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THESIS

FORECASTING CARRIER AIR-WING OPERATIONAL AVAILABILITY WITH EVENT STEP SIMULATION

By

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September 1999

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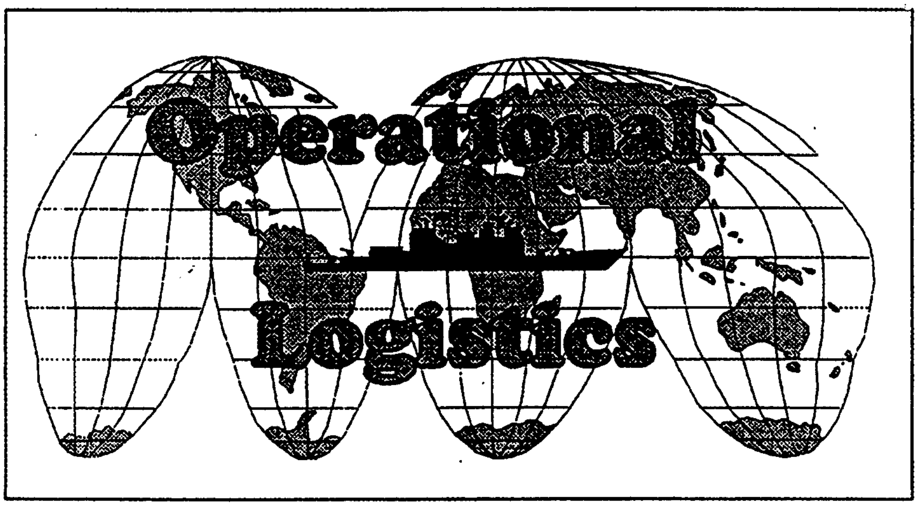
Amateurs discuss strategy,
Professionals study logistics



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FORECASTING CARRIER AIR-WING OPERATIONAL AVAILABILITY WITH EVENT STEP SIMULATION

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ABSTRACT

This thesis develops an event step simulation that models the Operational Availability (Ao) of carrier aircraft based on the supply and maintenance of Weapon Replaceable Assemblies (WRAs). It verifies that WRA allowances, developed by the Aviation Readiness Requirements Oriented to WRAs (ARROWs) model, achieve a target level of Ao given stated assumptions. It expands on ARROWs by characterizing not just the expected value of Ao but also its variability and probability distribution function. The simulation is expanded to include a variety of factors not considered by ARROWs. Examples of these factors include actual flight schedules, variable and prioritized requisitioning and repair, and cannibalization. The impact of these factors on the distribution of Ao is quantified. Simultaneous examination of all factors reveals that the full simulation predicts actual Ao approximately as well as ARROWs. In general, the full simulation overestimates Ao, and ARROWs underestimates Ao.

THESIS DISCLAIMER

The reader is cautioned that computer programs developed in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logic errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ACWT	Average Customer Wait Time
AIMD	Aircraft Intermediate Maintenance Department
AMRR	Aviation Material Readiness Reports
Ao	Operational Availability
ARROWs	Aviation Retail Requirements Oriented to Weapon Replaceable Assemblies
ATO	Air Tasking Order
AV3M	Naval Aviation Maintenance and Material Management
AVCAL	Aviation Consolidated Allowance List
BCM	Beyond Capability of Maintenance
CDF	Cumulative Distribution Function
CE	Cost Effectiveness
CNA	Center for Naval Analysis
DTO	Direct Turn-Over
EBO	Expected Backorders
EXREP	Expedited Repair
FMC	Full Mission Capable
JDK	Java Development Kit
MC	Maintenance Cycles
MC	Mission Capable
MRF	Maintenance Replacement Factor

MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
NAMP	Naval Aviation Maintenance Plan
NAVICP	Naval Inventory Control Point
NC	Not Carried
NIIN	National Item Identification Number
NIS	Not In Stock
NMC	Non Mission Capable
OS	Outstanding
OST	Order and Shipping Time
PDF	Probability Density Function
PMC	Partial Mission Capable
RBS	Readiness Based Sparing
RFI	Ready For Issue
RPF	Rotable Pool Factor
RTAT	Repair Turn Around Time
SCIR	Subsystem Capability and Impact Reporting
SRA	Shop Replaceable Assembly
TARPs	Tactical Air Reconnaissance Pod
TAT	Turn Around Time
TMS	Type Model Series
TTF	Time To Failure
WRA	Weapon Replaceable Assembly

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EXECUTIVE SUMMARY

The Aviation Readiness Requirements Oriented to Weapon Replaceable Assemblies (ARROWs) sparing model uses a Readiness Based Sparing (RBS) algorithm to develop allowance levels for major aircraft sub-assemblies. These major sub-assemblies are referred to as Weapon Replaceable Assemblies (WRAs). ARROWs allowance levels are intended to yield a target level of aircraft Operational Availability (Ao). The target level of Ao is an input to the model. The ARROWs output is a list of WRA allowances and a point estimate of the mean value of Ao they should provide.

The Ao actually achieved by fleet squadrons is frequently not the Ao predicted by ARROWs. This should not be surprising because Ao is a random variable. As such it should be characterized with a probability distribution not a point estimate. This thesis constructs an event step simulation that generates the probability distribution of Ao based on the supply and repair of WRAs. The baseline simulation produces a value of Ao equal to the point estimate provided by ARROWs, given the same assumptions.

The simulation expands on the ARROWs estimate of mean Ao by quantifying its variability, and its probability distribution function. Based on the simulation output, generic formulas are developed that allow ARROWs users to approximate the distribution of Ao without the benefit of a simulation.

While the ARROWs model necessarily contains a number of simplifying assumptions, the simulation is not so constrained. As such, the simulation is expanded to include a variety of factors that impact Ao but are assumed away by the ARROWs model. Examples of these factors include, actual flight schedules, prioritized

requisitioning and repair, variable order and shipping times, variable repair times and cannibalization. The use of historical data over assumptions is emphasized.

Each factor is examined independently by simulation excursions. The simulation excursions demonstrate how each factor changes the mean and variance of the distribution of Ao. Changes to the mean value of Ao are reflected by shifts of the Ao distribution away from the ARROWs point estimate. Changes in variability are reflected in a squeezing or stretching of the distribution about its mean value.

The ARROWs point estimate of Ao is not an accurate predictor of the Ao experienced by fleet aircraft squadrons. A final simulation excursion is developed to simultaneously include all of the functionality examined by the individual excursions. This full simulation is intended to serve as a forecasting tool for the level of Ao experienced by fleet aircraft squadrons. Comparison of the full simulation output to historical Ao data for fleet squadrons reveals that it, like ARROWs, does not accurately forecast actual Ao.

The full simulation provides estimates of mean Ao that are comparable in accuracy to ARROWs. On average, the simulation tends to overestimate mean Ao, and ARROWs tends to underestimate mean Ao. The full simulation expands on ARROWs by providing an estimate of Ao variability but that estimate is significantly less than the Ao variability observed by fleet squadrons.

The simulation developed by this thesis is relatively complex and incorporates a number of factors not addressed by ARROWs. Despite this added functionality, the simulation does not capture the truly complex system of operations, supply and maintenance taking place onboard an aircraft carrier.

I. INTRODUCTION

A. BACKGROUND

Operational Availability (Ao) is the percentage of time that an equipment or system is capable of performing its designed mission. This thesis examines the Ao of carrier based aircraft. The strict definition of Ao applies to a single aircraft. However, it is common practice to use the term Ao in lieu of mean Ao. Mean Ao is the average, or mean value of Ao for a group of like aircraft. Although most references to Ao actually refer to mean Ao, the term mean Ao is seldom if ever used. Distinguishing between Ao and mean Ao is important when examining the statistical properties of each.

In keeping with standard phraseology, this analyses makes frequent use of the term Ao with regard to carrier based aircraft. In all instances, these references refer to mean Ao. The Ao of individual aircraft are seldom discussed or examined. This point will be reiterated in statistical discussions where its importance is most significant.

Maintaining the Ao of carrier-based aircraft is essential to satisfying the Navy's operational requirements and accomplishing assigned missions. In order to achieve required levels of Ao for its carrier-based aircraft the Navy invests significant resources in repair parts and maintenance capability onboard aircraft carriers.

Carrier-based aircraft, like all weapons systems, are comprised of large numbers of sub-components. Each sub-component contributes to the aircraft's overall ability to perform its designed mission. The failure of any sub-component must be corrected in order to restore the aircraft to its full capability. Correction of such failures is accomplished by removing the failed item and replacing it with a Ready For Issue (RFI) unit. RFI items, removed from onboard supply stocks, are replaced by repair or requisition.

Aircraft sub-components are divided into two primary categories, Weapon Replaceable Assemblies (WRAs) and Shop Replaceable Assemblies (SRAs). WRAs are complex and very expensive aircraft sub-assemblies. When these units fail they are repaired and reused. SRAs are smaller, less expensive sub-components. Many SRAs are scrapped after failure. The focus of this thesis is the supply and maintenance of WRAs. SRAs will only be discussed as they pertain to WRAs.

Maintenance of aircraft onboard aircraft carriers is centered around WRAs. Organizational Level (O-Level) maintenance, conducted by squadron level personnel, consists largely of identifying and removing failed WRAs from aircraft and replacing the failed item with a Ready For Issue (RFI) WRA. RFI WRAs are obtained in a variety of different ways. The preferred and fastest method is that an RFI WRA is immediately drawn from the carrier's Supply Department. The next most desirable situation is that the failed WRA, removed from the aircraft, can be repaired by the carrier's Aircraft Intermediate Maintenance Department (AIMD or I-level maintenance) for expeditious reinstallation on the aircraft. In the event that an RFI WRA is not available from the Supply Department and the failed item cannot be repaired by the AIMD, a new WRA must be obtained from off the ship via the wholesale Supply System. [Ref. 1]

Each WRA is critical to the aircraft's ability to accomplish its mission [Ref. 2]. When a WRA fails, the parent aircraft is considered out of service or down. The duration of this downtime is determined by the time required to obtain a RFI WRA to remedy the failure. This downtime detracts from the amount of time the aircraft is capable of performing its mission (uptime). As downtime increases, the aircraft's Ao (percentage of total time the aircraft is up)

decreases. In order to maintain aircraft Ao at acceptable levels, the Supply and Maintenance Departments work together to ensure RFI WRAs are available with the least possible delay.

The number of spare WRAs carried by the Supply Department is obviously a significant contributor to the availability of RFI WRAs to support carrier based aircraft. If the number of spare WRAs were sufficiently large, aircraft downtime would be limited to the time required to remove failed WRAs and replace them with RFI WRAs. The high cost of spare WRAs makes such a system impractical. In an effort to conserve scarce resources, the Navy seeks to limit the number of spare WRAs stocked onboard the carrier to the minimum possible number required to achieve acceptable levels of aircraft Ao.

Supply Department stocking allowances for WRAs are published in the Aviation Coordinated Allowance List (AVCAL). AVCAL allowance quantities are developed by the "Aviation Retail Requirements Oriented to Weapon Replaceable Assemblies" (ARROWs) sparing model. ARROWs is a steady state, Readiness Based Sparing (RBS) model [Ref. 2]. It uses a variety of source data such as WRA failure rates, repair and re-supply times, air-wing composition, intended flight hour requirements and WRA unit costs to produce WRA allowances.

The ARROWs RBS algorithm attempts to identify the least expensive mix of spare WRAs that will enable the air-wing to realize a target or prescribed level of Ao. The Ao target is an entering argument to the allowance computation. This Ao target then serves as the predicted level of Ao expected to be realized by the computed set of WRA allowances. This point estimate of Ao is the only means available for forecasting the level of Ao expected from a given set of WRA allowances. If correctly computed, the point estimate of Ao is the expected value or mean Ao produced by the given WRA allowances.

The inventory, maintenance and repair of aircraft sub-assemblies represent a highly complex and variable system. The ARROWs computed allowance levels for WRAs do not, in many instances, result in the target or expected value of Ao being realized. This fact is unavoidable because Ao is not a fixed quantity but a random variable. In order to provide meaningful predictions of any random variable, including aircraft Ao, the Probability Distribution Function (PDF), expected value and variance, must all be characterized.

B. PURPOSE

This thesis constructs a robust model for forecasting aircraft operational availability based on the carrier's WRA allowances. Forecasts are made for each of the Type Model Series (TMS) embarked on the carrier. The model seeks to improve upon the availability calculations provided by ARROWs in two significant areas described below.

1. Characterize the Distribution of Ao

The level of Ao, achieved by carrier based aircraft routinely does not equal the value of Ao predicted by ARROWs. This fact should be expected because Ao is a continuous random variable not a constant. The probability that a continuous random variable will equal any discrete value is zero. The inability of ARROWs to characterize the distribution of Ao makes it a less robust indicator of Ao than is required. Identifying the distribution of Ao along with its mean and variance will allow forecasting Ao with a confidence interval vice a point estimate.

2. Quantify the Impact of Factors Not Considered in the ARROWs Model.

The primary function of ARROWs is to develop WRA allowances. In order to accomplish this function, ARROWs, like all models, depends on a variety of simplifying assumptions. Many of these simplifying assumptions concern factors that have a direct and

significant impact on Ao. Some of these factors are 1) ninety day support period, 2) uniform flight hour accumulation, 3) no prioritization of maintenance actions and supply requisitions, 4) mean values used in lieu of random variables for Order and Shipping Time and Repair Turn Around Time and, 5) no cannibalization.

By explicitly considering these factors, more meaningful predictions of Ao are possible. In addition to providing a better overall estimate of Ao, the impact of each of these significant contributors to Ao can be quantified.

C. MODEL

This thesis uses simulation to model the system of WRA supply and maintenance onboard an aircraft carrier. It then characterizes the performance of that system in maintaining aircraft operational availability. The simulation is based on data from the OCT97-MAR98 deployment of the USS GEORGE WASHINGTON (CVN-73) and her embarked air-wing.

Supporting data for the simulation was provided by the Naval Inventory Control Point (NAVICP), Philadelphia, PA. NAVICP is responsible for the inventory management of all repairables, including but not limited to WRAs, that support naval aviation. NAVICP operates and maintains the ARROWs allowance model and uses resulting allowance lists to publish AVCALs for use on the fleet's aircraft carriers. Data provided in support of this thesis includes WRA allowances developed for the WASHINGTON's AVCAL by ARROWs, aircraft configurations, and supporting source data.

This simulation develops Probability Distribution Functions (PDFs) for the level of TMS Ao achieved by a given mix of WRA allowances. The WRA allowances being examined are generated by the allowance model ARROWs. As such, the underlying assumptions of ARROWs are examined for potential inclusion in the model. Chapter II of this thesis provides a detailed

examination of how ARROWs generates WRA allowances and calculates the resulting Ao for each TMS. In addition, it lists and discusses the use of all source data and underlying assumptions about the carrier's supply and maintenance system made in the ARROWs model.

After the ARROWs model is well understood, the baseline simulation is developed. Chapter III details the development of the baseline simulation. The baseline simulation is written to replicate the ARROWs assumptions and calculated value of Ao, as closely as possible.

Chapter IV discusses the analysis conducted using the simulation. The baseline simulation attempts to replicate the ARROWs expected value of Ao and improve on it by characterizing its underlying PDF. This will be accomplished by running the baseline simulation using the ARROWs calculated WRA allowances and the same raw data and assumptions used in their determination. By running the simulation multiple times a mean or expected value of Ao can be determined and compared to that provided by ARROWS. The results of numerous simulations will also provide a range of observed values of Ao from which a standard deviation and a probability density function can be estimated.

ARROWs is an analytic model that uses closed form, steady state mathematical calculations. The complexity of the math involved dictates that ARROWs make use of numerous simplifying assumptions. Simulation is not similarly constrained. Once the baseline simulation and its associated distribution of Ao have been determined, the simulation is used to quantify the effect on Ao by the more complex factors previously listed.

Chapter IV describes how these more complex factors are incorporated into simulation excursions. Each simulation excursion independently examines the impact on Ao of a particular factor or assumption. As in the baseline simulation, each simulation excursion is run numerous times collecting Ao observations from which a revised distribution of Ao can be determined.

This new distribution is compared to the baseline distribution to determine the impact of the various factors on the distribution of Ao.

The final step in the analysis is to calculate the distribution of Ao with all of the functionality of the simulation operating simultaneously. This distribution of Ao serves as the best estimator of Ao available from the simulation. It is compared to the distribution of Ao determined in the baseline simulation, the value of Ao calculated by ARROWs, and the actual Ao data observed by the USS GEORGE WASHINGTON air-wing.

Chapter V summarizes the results of the analysis and presents conclusions formed as a result. It offers recommendations on how these conclusions can be utilized and gives recommendations for further study and analysis.

D. SCOPE AND LIMITATIONS

The simulation estimates the distribution of Ao for each TMS in a carrier deckload of aircraft. These Ao distributions are specific to a given set of WRA allowances. WRA allowances are developed by ARROWs based on a candidate file containing a wide variety of data including failure rates, repair times and prices. This source data is continually being changed and updated. The candidate file used by this thesis is specific to the USS GEORGE WASHINGTON's OCT97-MAR98 deckload. The deckloads and resulting WRA allowances are different for each carrier.

Characterizing the distribution of the random variable Ao allows greater understanding of the expected performance of a given allowance list. The results of this thesis apply to a specific air-wing and its associated deckload of aircraft and WRA allowances. However, the GEORGE WASHINGTON was selected due to the "standard" nature of its deckload. As such, conclusions will be drawn about the expected distribution of aircraft Ao on other carriers with ARROWs

generated WRA allowances. Quantifying the variance associated with an ARROWs predicted Ao is of particular interest. Other areas of interest are the overall impact of variations in the, Flying Hour Program, OST, TAT and Cannibalization on Ao.

The simulation developed by this thesis is fully capable of simulating other carrier deckloads and WRA allowances. However, the accomplishment of this tasking would be relatively labor and time intensive. The simulation is not designed for use by persons other than the author. Data input and output are considered cumbersome. This thesis is intended to demonstrate the value of simulation in forecasting aircraft Ao. In the event such a tool is desired for recurring analysis, a more user-friendly simulation with improved interfaces is required.

II. NAVICP ARROWS MODEL FOR AVCAL GENERATION

A. OVERVIEW

No dedicated tool for forecasting the Ao of carrier based aircraft is currently available for use by NAVICP or Fleet decision-makers. The only model that relates to Ao is the allowance list model ARROWs. ARROWs uses a target value of Ao as an input parameter. Ao target values are published in the Weapons System Planning Document [Ref. 3]. ARROWs develops WRA allowances that are intended to achieve the desired level of Ao at the minimum cost using a Readiness Based Sparing (RBS) algorithm.

For each Type Model Series (TMS) ARROWs provides a minimum cost set of spare WRAs intended to yield the target value of Ao. This Chapter details the source data, assumptions and calculations used by ARROWs in its assertion that the list of spares it has calculated will deliver the desired Ao target. Where appropriate, this information is incorporated in the baseline simulation.

B. ARROWS SOURCE DATA

The source data required for use by the ARROWs model is detailed in the P.C. ARROWs Users Manual, Volume IV [Ref. 2]. These data requirements support a wide range of ARROWs capabilities and functions. Only those data elements applicable to the ARROWs Type 2 Availability calculations are discussed here. Although ARROWs includes different methodologies for calculating Ao, the Type 2 calculation is the only method currently authorized for allowance development [Ref. 4]. Data used in the Type 2 ARROWs Ao calculation is described below.

1. The ARROWs Candidate File

The ARROWs candidate file provides information about all WRAs being considered for inclusion in the AVCAL. Entries in the candidate file correspond to particular WRA-to-aircraft combinations. Data in the candidate file is accumulated from a variety of sources including the Naval Aviation Maintenance and Material Management (AV3M) program and the Naval Aviation Maintenance Plan (NAMP). The following is a list of data elements associated with each entry in the candidate file along with a brief description of their use.

- <u>Type Model Series (TMS)</u>: TMS is the aircraft type on which an item is installed. If a WRA applies to an additional aircraft, another entry in the candidate file is required. Sorting the candidate file by TMS results in a list of all items applicable to a particular aircraft type (i.e., the TMS configuration).

- <u>National Item Identification Number (NIIN)</u>: The NIIN uniquely identifies this item in the Supply system.

- <u>Maintenance Cycles (MC)</u>: MC is the planned number of flying hours, of all aircraft of this TMS, on this carrier, for 90 days, divided by 100 (one MC equals 100 flying hours) multiplied by the number of applications per aircraft.

- <u>Maintenance Replacement Factor (MRF)</u>: MRF is the expected number of failures experienced by this item per 100 flying hours that are not able to be repaired by the

AIMD. Failures of this type must be sent off-ship for repair by a depot maintenance facility.

- Rotable Pool Factor (RPF): RPF is the expected number of failures experienced by this item per 100 flying hours that are able to be repaired by the AIMD.

- Turn Around Time (TAT): The average time in days required by the AIMD to repair this item. TAT includes time for processing, actual repair and time spent awaiting material.

- Price: The standard price of this item.

2. Site Parameter Data

Site data defines the carrier's deckload and operating environment. This data applies to all aircraft or all aircraft of a particular TMS.

- Order and Shipping Time (OST): The time in days required to fill an off-ship requisition. OST is currently set at 20 days. This figure applies to all TMS in the deckload.

- Mean Time To Repair (MTTR): The average time required by O-level maintenance personnel to remove a failed WRA and replace it with an RFI WRA. MTTR varies by TMS.

- Number on CV: The quantity of a particular TMS in the deckload.

- Fully Mission Capable Goal: Naval Aviation commonly expresses Operational Availability in two ways, 1) Fully Mission Capable (FMC), and 2) Mission Capable (MC). FMC is the percentage of time an aircraft is capable of performing all assigned missions. MC is the percentage of time an aircraft is available to perform some, but not all of its missions. The ARROWs Type 2 Ao calculation is equivalent to FMC. ARROWs uses the FMC goal as the Ao target value. The FMC goal varies by TMS.

C. ARROWS ASSUMPTIONS

Like all models, ARROWs depends on a variety of simplifying assumptions. In order to replicate ARROWS to the greatest extent possible, these assumptions are documented and included in the baseline simulation. Many of ARROW's assumptions are dictated by the closed form analytic calculations made by the model. Simulation does not make use of these calculations allowing relaxation of corresponding assumptions. Listed below are the assumptions used by ARROWs to develop WRA allowances.

1. ARROWs is a Steady State Model

ARROWs models the carrier's supply maintenance system as a stochastic queuing process. Failed WRAs arrive, await service (which equates to obtaining an RFI WRA) and then exit the system. Probabilities concerning the number of system arrivals and their service times are limiting or steady state values.

2. WRA Failures Form a Poisson Process:

The arrival of failed WRAs to the carrier's supply-maintenance system is modeled as a Homogeneous Poisson Process. This implies that the time between WRA failures is exponentially distributed and that arrivals are always single WRAs. ARROWs requires this assumption for probability calculations involving the number of system arrivals. Failures of individual WRAs are independent of one another and are also independent of time spent in the supply-maintenance system.

3. All Requisition and Repair Times are Constants

ARROWs uses constant values for OST and TAT. These times represent the average or mean time expected to complete an off-ship requisition or repair action based on historical data. ARROWs assumes time to complete a stock issue, time to initiate requisitions and time to initiate repairs are zero. These times are negligible or are embedded in the OST and TAT values.

4. Additional Assumptions and Characteristics of ARROWs

The ARROWs Type 2 Ao calculation assumes that WRAs can fail while an aircraft is down. ARROWs' calculations place no limit on the repair capacity of the carrier's AIMD. In addition, ARROWs provides no information on the amount of repair capacity required to maintain the WRA allowances it computes.

The number and types of aircraft are constant in all ARROWs computations. ARROWs does not apply flight hours to individual aircraft. The entire flying hour program is applied to the individual WRAs that make up the TMS configuration. Multiple applications of the same WRA, on this TMS, are accounted for with an increase in flying hours proportional to the number of installations. A total number of failures for the individual WRA is calculated. Based on total

failures and the number of spares carried, the availability of individual WRAs (a_o) is computed and used to calculate the Ao of the entire aircraft. The end result is that the flight hour program is uniformly distributed over all aircraft in a TMS.

D. ARROWS TYPE 2 Ao CALCULATION

The description of the ARROWs availability calculations described below is provided for background use only. It is intended to demonstrate the methodology used by ARROWs to calculate Ao. A more thorough derivation of these concepts is available in the PC ARROWs Users Manual [Ref. 2].

1. Overview

The Ao required for each TMS is an ARROWs input. The ARROWs RBS algorithm desires an optimal solution to the following problem.

Min: *Cost of the WRA allowance list*

ST: *TMS Availability ≥ Target Ao*

ARROWs uses marginal analysis to solve this problem and a true optimal solution may or may not be obtained. TMS availability is continuously re-evaluated, based on the addition of more WRAs, using the ARROWs Type 2 Ao calculation. When TMS availability exceeds the Ao target, the solution to the problem is the list of WRA allowances on which the TMS Availability is based.

The ARROWs Type 2 Ao calculation is based on two assumptions 1) all WRA failures are independent, and 2) all WRAs installed on an aircraft are required for that aircraft to be operational. Operational in this context equates to FMC. The Ao target is the FMC goal obtained in the ARROWs site parameter data for each TMS. These assumptions allow the

aircraft to be modeled as a series structure [Ref. 5:p. 476]. The probability that a series structure is functioning is then the product of the probabilities that each of its components is functioning. The Ao for each TMS is computed as follows:

$$A_o = \prod_{i=1}^{n} a_{o_i} \quad ,$$

where,

Ao = operational availability for a given TMS;

a_{oi} = operational availability for WRA_i (all applications for this TMS);

n = the number of WRAs in the TMS being examined.

In order to calculate the Ao for a TMS, ARROWs must first calculate the individual availability's of all its installed WRAs. These calculations are based on queuing theory. Calculations are performed on each type of WRA separately. In other words, each WRA type is treated as having its own queue. Little's formula states [Ref. 5:p. 413],

$$L = \lambda * W$$

where,

L = the average number of WRAs in the system;

λ = the average arrival rate of entering WRAs;

W = the average amount of time a WRA spends in the system.

In this system, L is the average number of failed WRAs, of a given type, in the supply-maintenance system. This term is commonly referred to as "pipeline"; λ is the rate at which WRAs of this type arrive at the system; W is the average time it takes to provide an RFI WRA.

Each WRA type has its own unique values for these variables. Given this queuing system and the assumptions stated in paragraph II.C.2, the number of WRAs in the system is Poisson distributed. The probability that N WRAs are in the system at any time is obtained using Palm's Theorem as follows:

$$P(N = n) = \frac{e^{-L} * L^n}{n!} ,$$

where,

n = number of WRAs, of this type, in the system;

L = pipeline, for this WRA [Ref. 6:p. 460].

2. Pipeline

Pipeline refers to the average number of WRAs in the supply-maintenance system. Pipeline is divided into two parts, supply pipeline and repair pipeline. Supply pipeline represents the average number of WRAs, of this type, awaiting the receipt of an off-ship requisition. Supply pipeline is computed as follows:

$$L_S = \frac{MRF * MC * OST}{90 Days} .$$

Repair pipeline represents the average number of WRAs, of this type, awaiting repair by the carrier's AIMD. Repair pipeline is computed as follows:

$$L_R = \frac{RPF * MC * TAT}{90 Days} .$$

Total pipeline is simply the sum of supply pipeline and repair pipeline, noted below.

$$L = L_S + L_R$$

3. Expected Backorders

Failed WRAs arrive at the supply-maintenance system and await an RFI asset to be made available. If an RFI asset is on-hand in the Supply Department, wait time is zero and the failed WRA bypasses the queue. Failed WRAs for which no stock is on-hand in the Supply Department enter the queue and are called backorders. An off-ship requisition or a completed repair must be received to fill each backorder. Backorders are serviced on a first come first serve basis. In the case where no stock is carried, Expected Backorders (EBO) is equal to expected demand. As the inventory level of each item of stock increases its depth, the EBO decreases.

ARROWs is an allowance development model. EBO is calculated based on the allowance for the WRA being examined which is not known at the time the model is run. As such, ARROWs calculates the EBO for each item of potential stock carried and saves these values for later use. EBO is calculated for each item of potential stock carried until its value is negligible. EBO is calculated as follows:

$$EBO = \sum_{x=S+1}^{\infty} (x - S) * P(X = x) \ ,$$

where, S = Quantity of WRAs stocked (i.e., allowance quantity).

Substituting Palm's theorem from above, the equation for EBO becomes,

$$EBO = \sum_{x=S+1}^{\infty} (x - S) \frac{e^{-L} * L^{x}}{x!} \ .$$

4. Average Customer Wait Time

From Little's formula, the average waiting time for all WRA failures is the pipeline divided by the arrival rate of all WRAs. If EBO is substituted for total pipeline then the average

waiting time for backordered items is obtained. The time required to satisfy a backorder is the Average Customer Wait Time (ACWT), noted below,

$$ACWT = \frac{EBO}{\lambda} \ ,$$

where, $\lambda = (MRF+RPF)*MC$.

As with EBO, ACWT is dependent on the number of spare WRAs stocked on the carrier. ACWT is computed for all levels of potential sparing, and these values are saved for use in allowance development.

5. WRA Operational Availability

WRA Operational Availability (a_o) is the percent of time a WRA is available to perform its mission. Ao is normally calculated at the aircraft or system level but ARROWs examines the a_o of each WRA. WRA a_o is a function of EBO. ARROWs calculates EBO for all levels of potential stocking and likewise calculates a_o for each value of EBO. This range of a_o's is saved for use in calculating Ao at the TMS level. WRA a_o is computed as follows:

$$a_o = \frac{1}{1 + \dfrac{(Failures * MTTR) + EBO}{\# ofAircraft}} \ .$$

6. ARROWs Allowance Development

ARROWs is an RBS sparing model. As such, it seeks to minimize the total cost of all spare WRAs carried subject to achieving the target Ao for each TMS. To accomplish this, ARROWs computes a Cost Effectiveness (CE) ratio for each WRA potentially stocked. CE ratio

is a measure of improved readiness per dollar spent on spares. CE ratio is calculated using the following equation for each WRA stocking level:

$$CE = \frac{Price}{(\text{Decrease in ACWT}) * (\text{MRF} + \text{RPF}) * \text{MC}},$$

where, Decrease in ACWT = the reduction in ACWT by adding one unit of Stock to the allowance list.

Once the CE ratios for a given WRA and each level of potential stock, for that WRA, are computed, the entire process described above is repeated for each WRA in the TMS configuration. When all WRAs have been examined each WRA has a CE ratio for each unit of stock that may potentially be carried. These CE ratios are then ranked from lowest to highest. This list of stock selections is called the "ARROWs shopping list".

Using the ARROWs shopping list, WRAs are selected for stocking based on their CE. As each item of stock is added, a_o for that WRA is increased. This results in a corresponding increase in the product of all WRA a_o's, raising the overall Ao of the TMS being considered. When Ao reaches the FMC Goal, (the Ao target selected by the user for this TMS) the process is complete. For the TMS under consideration, the expected Ao equals the FMC goal.

7. Allowance Development for Multiple TMS

The methodology for calculating WRA allowances to support multiple TMS is not specifically identified in the PC ARROWs Users Manual. In general, the user selects the order in which ARROWs will spare the various TMSs. The first TMS evaluated is done so according to the description above. Subsequent TMSs use the allowances computed for previous TMSs as a cumulative input. For parts common to more than one TMS, the cost and readiness contributions

are prorated over all applicable TMSs according to their relative demands. If each TMS is being spared to an Ao target, which is normally the case, this method will create a total WRA mix that supports higher Ao levels than specified by the individual TMS targets. [Ref. 7:p. 4]

III. SIMULATION MODEL DEVELOPMENT

A. OVERVIEW

The purpose of this simulation is to characterize the distribution of Ao for carrier based aircraft. Aircraft Ao is assumed to be solely dependent on the operability of installed WRAs. This simulation models the operation of aircraft to simulate usage and failure of installed WRAs. Further, it models the ability of the supply-maintenance system to provide RFI WRAs when installed WRAs fail. The effectiveness with which this is accomplished will determine the observed Ao of individual aircraft and overall mean Ao for each Type Model Series (TMS).

1. Programming Tools

The simulation is written in Java using the Java Development Kit (JDK) Version 1.2 [Ref. 8]. Java is an object oriented programming language well suited for use in simulation. To ensure readability by persons with a limited programming background, the simulation descriptions offered in this Chapter make no references to Java coding or Java specific terminology.

In addition to the JDK, this simulation utilizes another software package, SIMKIT Version 1.0 [Ref. 9]. SIMKIT is written in Java and provides a collection of programming tools used in developing event-based simulations. Event-based simulations use specific events, not fixed time increments, to advance through the simulation [Ref 10:p. 3]. SIMKIT provides the underlying event list and event handling software to support the simulation.

2. The Baseline Simulation

As previously stated, Java is an object oriented programming language. The Java objects created in this simulation are easily related to actual objects on the aircraft carrier. These objects

are aircraft, the air-wing, the Air Tasking Order (ATO), the Supply Department and the Aviation Intermediate Maintenance Department (AIMD). The simulation builds these objects to behave and interact much as they would on an actual aircraft carrier.

The methodology of the baseline simulation is described in this Chapter by describing each of the simulated objects. References to simulated objects in this Chapter are *italicized.* This convention allows the reader to distinguish between simulated objects and the physical objects they represent. Departures from assumptions used by the ARROWs allowance model will be noted as they appear in the object descriptions. The description of each object follows this format.

- Data Requirements: Describes the source data required to create the object and how that data is stored and managed for use during the simulation.
- Functionality: Describes what this object does in the simulation and how it is done. It also describes how this object interacts with other objects and the results of those interactions.
- System Performance Measures Available for Output: Lists the useful data available from this object at the conclusion of the simulation.

B. BASELINE SIMULATION OF *AIRCRAFT* OBJECTS

Each *aircraft* in the *air-wing* is modeled as a discrete object. All *aircraft* are handled by the simulation in the same manner and share the same functionality. There are nine different types of *aircraft* corresponding to the nine different TMSs represented in the carrier deckload. The number and types of *aircraft*, along with their ARROWs Ao target, are provided in Table 1.

TMS	Name	Quantity	ARROWs Ao Target
EA6B	Prowler	4	.600
ES3A	Shadow	2	.600
RF14B	Tomcat (TARPs)[1]	8	.560
E2C2	Hawkeye	4	.560
F14B	Tomcat	12	.640
FA18C	Hornet	36	.660
S3B	Viking	8	.560
HH60H	Seahawk	2	.600
SH60F	Seahawk	3	.660

Table 1. USS GEORGE WASHINGTON Deckload Composition

1. *Aircraft* Data Requirements

The primary data used to construct an *aircraft* is the TMS WRA configuration and the failure rates associated with those WRAs. This data is obtained from the ARROWs candidate file. Three parallel arrays are created in each *aircraft* to hold part number, Mean Time To Failure (MTTF) and Time To Failure (TTF) for each WRA installed in its applicable TMS.

Each element in the parallel arrays corresponds to an installed WRA. If a WRA has multiple installations, it will appear as an element in the arrays the appropriate number of times. This is a departure from ARROWs which handles multiple installations by an appropriate increase in Maintenance Cycles (MC). The parallel arrays are populated in the following manner. Part number is a pseudonym to the WRA NIIN assigned for the simulation. MTTF is calculated by combining the MRF and RPF found in the candidate file. TTF is obtained by sampling from an exponential distribution with mean value equal to MTTF.

[1] Tactical Air Reconnaissance Pod (TARPs)

Other data required by each *aircraft* are tail number and Mean Time To Repair (MTTR). Tail numbers are assigned by the *air-wing* when *aircraft* are constructed. Tail numbers range from one to the number of each TMS in the deckload, for each TMS. The MTTR is constant for all *aircraft* of a given TMS and is available in the ARROWs site parameter data.

2. *Aircraft* Functionality

a. *Aircraft* Fly Sorties

The primary function of an *aircraft* is to fly sorties. Sorties are assigned by the *air-wing* and commence at the time of tasking. A sortie is assigned to an *aircraft* if, and only if, that *aircraft* is in an "up" status. Once a sortie is assigned, the *aircraft* immediately schedules an end of sortie event at the appropriate time. At this time, the *aircraft* applies the flight hours incurred during the sortie to all of its installed WRAs. This is accomplished by looping through the *aircraft's* array of TTFs and decrementing each by the number of flight hours incurred by the *aircraft*.

b. *Aircraft* Monitor Installed WRAs for Failures

Aircraft remain in an "up" status if the TTF for all installed WRAs is greater than zero after a sortie. *Aircraft* remaining in "up" status are immediately available for additional sortie assignments. Sortie requirements, duration and frequencies are discussed in the *air-wing* and *ATO* objects. In the event one or more TTFs are less than or equal to zero, the applicable WRA(s) is considered failed and the *aircraft* is "down". Once an *aircraft* is "down" it cannot be assigned sorties and therefore its WRAs incur no additional flight hours. As a result, WRAs

cannot fail while an *aircraft* is "down". This is in contrast to the ARROWs assumption that WRAs can fail while an aircraft is "down".

Once an *aircraft* is "down" it remains so until such time as the replacement WRA(s) it requires is provided. The means by which RFI WRAs are made available is described in detail later in the Chapter. When a RFI WRA is made available to a "down" *aircraft*, the new asset is installed by re-sampling from the exponential distribution with the appropriate MTBF for that WRA. This value is then recorded in the appropriate location in the TTF array. If an additional RFI WRA is required, the *aircraft* remains "down" until that asset is made available. If this was the only replacement WRA required by the *aircraft*, the *aircraft* is returned to an "up" status in one MTTR.

The minimum time an *aircraft* can be in a "down" status is one MTTR. This occurs when the RFI WRA(s) required by the *aircraft* is available from the *Supply Dept.* In all other instances, downtime is the sum of MTTR and the time to furnish the required RFI WRA(s).

3. *Aircraft* System Performance Measures Available for Output

Each *aircraft* maintains a record of sorties flown, hours flown and airframe Ao. Examination of these values is used primarily for troubleshooting. The *Air-Wing* provides these same statistics for each TMS as a whole.

C. BASELINE SIMULATION OF THE *AIR-WING*

The *air-wing* consists of arrays of *aircraft* objects. Each TMS in the deckload has a corresponding array in the *air-wing*. The number of *aircraft* in each TMS array is the number of that TMS in the deckload. The *air-wing* also contains an array of "down" *aircraft*. *Aircraft* of

any TMS are added to this array at the time of failure and removed from this array when they are returned to an "up" status.

1. *Air-Wing* Data Requirements

The quantity of each TMS in the deckload is required to construct the *air-wing*. The *air-wing* uses these quantities to construct the required *aircraft* for each TMS. These *aircraft* are then used to populate their corresponding arrays. The quantity of each TMS is found in the ARROWs site parameter data..

Also required for *air-wing* construction is the sortie duration for each TMS. The *air-wing* uses this data in the scheduling of *aircraft* sorties. This figure is set at two hours for all TMS in the baseline simulation.

2. *Air-Wing* Functionality

a. *Air-Wing* Assigns Sorties to *Aircraft*

The *air-wing* receives flight schedule requirements at the start of each day. Requirements are provided by the *ATO* in the form of pairs of integers. The first integer represents the TMS for which the sorties apply and the second is the number of sorties assigned. The *air-wing* loops through the applicable TMS array and attempts to assign sorties. Each *aircraft* is queried to determine if it is in an "up" status. If an *aircraft* is "up", it is assigned a sortie and the sorties required quantity is decremented. If an *aircraft* is "down", the *air-wing* moves on to the next *aircraft* in the TMS array.

If all sorties for a TMS were satisfied in the first loop through the TMS array, the *air-wing* is through with that TMS until the start of the next day. Otherwise, the *air-wing* saves

the number of sorties not assigned for assignment later in the day. After waiting one TMS sortie duration, the *air-wing* attempts to assign remaining sorties. In the interim, *aircraft* previously "down" can be repaired and aircraft assigned earlier sorties can fail. This process continues until all sorties are assigned or there is no time left in the day to fly them.

The number of sorties an *aircraft* can be assigned in one day is limited to three. This is consistent with actual practice. As *aircraft* in the simulation fail, *aircraft* in an "up" status incur additional sorties to meet the required flying hour program. If the sorties are unable to be assigned on the day scheduled then the sorties are scrubbed. The simulation does not forward sorties to the next flying day. This convention results in a potential decrease in total flying hours incurred for this TMS throughout the simulated period. If this phenomenon were significant, it would bias the estimate of Ao by rewarding poor Ao on a given day with reduced flight hours. Numerous simulation runs reveal that the loss of scheduled sorties is a rare event. When observed, the percent of total flight hours lost is negligible.

The *air-wing* attempts to distribute flying hours equitably among all *aircraft* within each TMS. Flight hours vary by *aircraft* because sortie assignment depends on whether the *aircraft* is "up" or "down". *Aircraft* that are "down" for extended periods incur less flight hours than *aircraft* that are not. What can be accomplished is that all *aircraft* are potentially assigned the same amount of sorties. The *air-wing* accomplishes this by recording where in the TMS array the last sortie assignment was made. The next time a sortie needs to be assigned, the *air-wing* checks the next *aircraft* in the array, instead of continually checking the early elements in the array first. Addition of this feature to the simulation markedly improved flight hour distribution among the *aircraft* of each TMS.

b. *Air-Wing* Tracks "Down" *Aircraft*

The *air-wing* is notified when any *aircraft* is "downed". At this time, the *air-wing* places a copy of this *aircraft* in the "down" *aircraft* array and an observation of a time varying statistic for the number of "down" *aircraft* for each TMS is made. A similar observation is recorded when the *aircraft* is returned to an "up" status. This statistic allows the *air-wing* to calculate Ao for each TMS. The "down" *aircraft* array is also used by the *air-wing* in the distribution of RFI WRAs to the *aircraft* that require them.

c. *Air-Wing* Distributes RFI WRAs

RFI WRAs are made available to the *air-wing* not to individual *aircraft*. This allows the *air-wing* to prioritize between two *aircraft* that require the same WRA. Priority is given to *aircraft* that will be returned to an "up" status with receipt of this WRA. If more than one *aircraft* fall into this category, preference is given to the TMS with lowest current value of Ao. If all the *aircraft* are of the same TMS, the selection is based on position in the "down" aircraft vector. If no *aircraft* will return to an "up" status with the receipt of this WRA (i.e. additional WRAs are required for repair), priority is again given to the *aircraft* whose TMS has the lowest current value of Ao.

3. *Air-Wing* System Performance Measures Available for Output

The *air-wing* calculates and reports the value of Ao for each TMS. TMS Ao is the simulation's primary performance measure. The *air-wing* also calculates sorties and hours flown by TMS. These figures are used primarily for troubleshooting. In the majority of simulation runs, these values are equal to the sorties and flight hours assigned by the *ATO*. In instances where these values are not the same, the differences are negligible.

D. BASELINE SIMULATION OF THE *AIR TASKING ORDER (ATO)*

The *ATO* passes daily flight requirements to the *air-wing* for assignment and execution.

1. *ATO* Data Requirements

The data required to construct the *ATO* is the flying hour program for each TMS. The ARROWs candidate file contains the Maintenance Cycles (MC) for each TMS. MC is the number of flight hours required during a 90 day period by all aircraft of a particular TMS times 100. The *ATO* distributes these flight hours evenly across the 90-day period. Average sortie duration is assumed to be two hours for all TMS. Therefore, the number of sorties required by each TMS per day is,

$$TMS\_Sorties / Day = \frac{(MC)(100hrs)}{(2hrs)(90days)} .$$

The number of sorties per day must be an integer. In cases where this is not true, the requirements must be adjusted accordingly. For example, MC for the *ES3A* is 6. Two *ES3As* are available to meet this requirement. TMS_Sorties/Day = 3.33. The most even distribution of integer values equates to 69 days with 3 sorties and 21 days of 4 sorties. These sortie requirements are spread over the 90-day period such that heavy and light flying days are evenly dispersed.

The final format of the data is a matrix of TMS sortie requirements. Rows in the matrix represent a day of a month and columns represent TMS. The number of matrices is equal to the number of thirty-day months being simulated.

2. *ATO* Functionality

The function of the *ATO* is to provide daily sortie requirements, for each TMS. These requirements are passed to the *air-wing* for assignment to individual *aircraft* and execution. At the start of each day, the *ATO* passes a grouping of ordered pairs of integers to the air-wing. These ordered pairs equate to a TMS type code and a number of sortie requirements for that TMS. The TMS type code is the column number of the sortie requirement matrix. This process continues until all requirements have been passed.

3. *ATO* System Performance Measures Available for Output

The *ATO* does not track or report any system performance measures.

E. BASELINE SIMULATION OF THE *SUPPLY DEPARTMENT*

The *Supply Dept.* provides RFI WRAs to the *air-wing* for use in repairing *aircraft*. RFI WRAs are obtained in one of three ways, 1) issue of an onboard spare, 2) issue of a repaired WRA carcass, or 3) turnover of a Direct Turn-Over (DTO) requisition received from off-ship. The *Supply Dept.* also interacts with the *AIMD* in managing the repair of failed WRAs.

1. *Supply Department* Data Requirements

The *Supply Dept.* is constructed using a list of all WRAs installed on any TMS and an allowance value for those WRAs. The list of WRAs is obtained from the ARROWs candidate file and allowance values are an ARROWs output. When the *Supply Dept.* is constructed, a matrix is developed to manage and track each WRA. The rows in the matrix correspond to the WRA part number. WRA part numbers are locally assigned aliases for WRA NIINs. Each unique WRA is represented by a single row in the matrix regardless of the number installed on

one or more TMS. The columns in the matrix correspond to WRA specific counters. These counters include.

- On-hand balance
- Allowance
- Due in (from an *AIMD* stock repair or stock requisition)
- Outstanding (OS) DTO requisitions
- EXREPs in *AIMD*

The allowance counter is never adjusted. This value allows the *Supply Dept.* to reset itself at the beginning of each simulation run. On-hand balances, for all WRAs, are initially set equal to the WRA allowance value. All other counters are set equal to zero.

The *Supply Dept.* also requires values for numerous time parameters. The most significant of these values is Order and Shipping Time (OST). The OST is obtained from the ARROWs site parameter data and is equal to 20 days in the baseline simulation. This value of OST applies to both stock and DTO requisitions. Other time parameters include 1) time required to make an issue, 2) time required to pass material to the AIMD, 3) time to generate requisitions, and 4) time required to turnover material to the air-wing. Consistent with ARROWs, these values are all set equal to zero in the baseline simulation.

2. *Supply Department* Functionality

a. *Supply Dept.* Issues on-hand Material and Forwards Carcasses to the *AIMD* for Repair

Individual *aircraft* notify the *Supply Dept.* of WRA failures. This notification happens with no delay and includes the part number of the failed WRA. Note that all WRA

requirements are for one each. If multiple WRAs of the same type fail in the same sortie, the *Supply Dept.* is notified multiple times. This is a departure from the ARROWs model in that multiple failures of the same WRA never occur. ARROWs handles multiple installation of the same WRA on an aircraft by increasing the rate that item fails proportional to the number of installations.

The *Supply Dept.* immediately checks the on-hand balance to determine if an issue can be made. If material is available the on-hand balance counter is decremented and the RFI WRA is passed to the *air-wing* for distribution to the requiring *aircraft*. Simultaneously, the applicable Due in counter is incremented, and the *Supply Dept.* notifies the *AIMD* to begin a stock repair action for the WRA carcass.

If an RFI asset is not available for issue, the *Supply Dept.* examines the allowance value for this WRA to classify the demand as Not Carried (NC) or Not In Stock (NIS). The failed WRA is then passed to the *AIMD* to attempt an Expedited Repair (EXREP) and the EXREPs in *AIMD* counter is incremented. Note that the *Supply Dept.* is able to distinguish between stock and EXREP repairs. This functionality is included for simulation excursions. In the baseline simulation, like ARROWs, repairs of stock and EXREP carcasses are completed by the *AIMD* in one Turn Around Time (TAT).

b. *Supply Dept.* Generates Requisitions

(1) Generates Stock Replenishment Requisitions

Stock replenishment requisitions are generated by the *Supply Dept.* when it is notified by the *AIMD* that a stock repair action is unable to be performed. This notification

provides the applicable WRA part number. The *Supply Dept.* then schedules the arrival of the stock replenishment requisition in one OST.

(2) Generates Direct Turn-Over (DTO) Requisitions

Direct turnover requisitions are generated when the *Supply Dept.* is notified by the *AIMD* that an EXREP was unable to be effected. The outstanding direct turnover requisition counter is incremented and the EXREPs in *AIMD* counter is decremented. The receipt of the direct turnover requisition is scheduled in one OST. The *Supply Dept.* distinguishes DTO from stock requisitions for use in simulation excursions. In the baseline simulation, like ARROWs, all requisitions, regardless of type, arrive in one Order and Shipping Time (OST).

c. *Supply Dept.* Receives and Distributes RFI WRAs

The *Supply Dept.* receives RFI WRAs from two sources, the *AIMD* and the wholesale supply system. Receipts are further distinguished as to whether they are intended for DTO or stock. Regardless of source or original intended recipient, all WRA receipts are handled in a similar fashion. This allows the *Supply Dept.* the capability to efficiently divert stock receipts to fill DTO requirements. DTO requirements can be outstanding DTO requisitions or EXREPs in the *AIMD* under repair. Use of a WRA intended for stock to satisfy either type of DTO requirement is termed a Stock Divert.

Stock Diverts are critical to achieving the level of A_O calculated by ARROWs. ARROWs does not link individual WRA failures to a specific receipt time in the future. Instead, it uses the pipeline concept, described in Chapter II, to evaluate the expected time required for the next WRA, of this type, to become available from any source. This is consistent with the

actual supply-maintenance system onboard the aircraft carrier. The AIMD's Production Control Officer and the Supply Dept.'s Aviation Support Officer (S-6) manage the use and disposition of all RFI WRAs to ensure all DTO requirements are satisfied in the most timely manner possible.

The *Supply Dept.* is notified by the *AIMD* when a stock repair action has been completed. The *Supply Dept.* examines the outstanding DTO and EXREPs in the *AIMD* counters to determine if a DTO requirement for this WRA exists. If either counter is greater than zero the WRA, just received for stock, is required to repair an *aircraft*. In this case, the *Supply Dept.* increments the Stock Diverts counter and passes the WRA to the *air-wing* for distribution. If no DTO requirement for this WRA exists, it is received for stock by incrementing the on-hand balance counter and decrementing the Due In counter. Receipts for stock requisitions are handled in the same manner as stock receipts from the *AIMD*.

The *Supply Dept.* is notified by the *AIMD* of completed repairs to an EXREP WRA. The *Supply Dept.* examines the applicable EXREP in *AIMD* counter to determine if an EXREP DTO requirement still exists. If so, the *Supply Dept.* decrements the EXREP in AIMD counter and forwards the WRA to the *air-wing* for distribution. If the EXREP in AIMD counter is equal to zero, the outstanding DTO requisition counter is checked. If a DTO requirement of this type exists, the Stock Diverts counter is incremented and the WRA is passed to the *air-wing*. Note, use of a completed EXREP to fill an outstanding DTO requisition is a Stock Divert because the completed EXREP is intended as a payback for a previously diverted WRA. If the outstanding DTO requisition counter is likewise equal to zero, the WRA is placed in stock by incrementing the on-hand balance counter and decrementing the Due In counter. Receipt of a DTO requisition is handled in the same manner as the receipt of a repaired EXREP WRA through adjusting the corresponding counters.

3. *Supply Department* System Performance Measures Available for Output

The *Supply Dept.* tracks performance through six department total counters. These counters include,

- Total Issues
- Total NIS
- Total NC
- Total off-ship stock replenishment requisitions
- Total off-ship DTO requisitions
- Total Stock Diverts

These statistics are reported for each simulation run. The off-ship requisition totals, stock and DTO, are used as indicators of supply-maintenance system performance in supporting the *air-wing*. The totals for issues, NIS and NC are used to compute Supply Net and Gross Effectiveness. These performance statistics measure the *Supply Dept.*'s ability to meet demands. They are calculated as follows:

$$Gross\_Eff = \frac{Total\_Issues}{(Total\_Issues) + (Total\_NIS) + (Total\_NC)}$$

$$Net\_Eff = \frac{Total\_Issues}{(Total\_Issues) + (Total\_NIS)}.$$

Total Stock Diverts are used to gauge what percent of requirements, not filled by an issue from stock, are satisfied earlier than would be expected due to the efficient distribution of RFI WRA assets by the supply-maintenance system.

F. BASELINE SIMULATION OF THE *AIMD*

The *AIMD* receives WRA carcasses from the *Supply Dept.* for repair. Repair actions are of two types, stock replenishment and EXREP. If repairs can be effected, an RFI WRA is returned to the *Supply Dept.* in one Turn Around Time (TAT) for appropriate distribution. Note that in the baseline simulation, as in ARROWs, EXREP and stock replenishment repair action take the same amount of time to complete. If repairs cannot be made, the *Supply Dept.* is notified so the appropriate off-ship requisition can be generated.

1. *AIMD* Data Requirements

The *AIMD* is constructed using the same comprehensive list of WRAs developed for the *Supply Dept.* WRAs are identified by their locally assigned part numbers. In addition to part number, the *AIMD* requires the TAT, Maintenance Replacement Factor (MRF) and Rotable Pool Factor (RPF) for each WRA. All data requirements are obtained from the ARROWs candidate file. A matrix is constructed to hold the required data. Rows in the matrix correspond to each WRA. The columns represent TAT, MRF and RPF.

2. *AIMD* Functionality

a. Repairs WRAs for Return to *Supply Dept.* Stocks

The *AIMD* is notified by the *Supply Dept.* that a failed WRA requires repair for return to stock. Prior to initiating repair, the *AIMD* determines if repair is possible. A random number is generated between zero and one. This number is then compared to the proportion of total failures, for this WRA, that can be repaired. The proportion able to be repaired is calculated as follows:

$$Proportion\_Repairable = \frac{RPF}{RPF + MRF} \ .$$

If the random number is less than the proportion repairable, the WRA can be repaired. The *AIMD* schedules the delivery of the repaired WRA to the *Supply Dept.* in one TAT. If the random number is greater than the proportion repairable, the WRA cannot be repaired. The general term for this case is Beyond Capability of Maintenance (BCM). In this instance, the *Supply Dept.* is immediately notified that the stock replenishment repair action could not be effected. The *Supply Dept.* will in turn generate the appropriate requisition to replace this WRA from off-ship.

b. Repairs WRAs for Immediate Use by an Aircraft (EXREP)

EXREP repair actions are handled in the exact fashion as stock repair actions. The *AIMD* first determines if repairs can be made. Based on this determination it schedules delivery of the RFI WRA in one TAT or immediately notifies the *Supply Dept.* that repair of an EXREP could not be effected. Stock and EXREP repair actions are differentiated to provide additional functionality in later variations of the simulation. In the baseline simulation the only functionality added is that *Supply Dept.* is able to distinguish between DTO and stock requirements.

3. System Performance Measures Available for Output

The *AIMD* uses a variety of counters to collect data on repair activities conducted. These counters are listed below.

- Total EXREP inductions
- Total EXREP Beyond Capability of Maintenance (BCM)

- Total EXREP repairs
- Total stock inductions
- Total stock BCMs
- Total stock repairs

The *AIMD* also makes use of two time varying statistics, one for stock and one for EXREP. These statistics are used to measure the average amount of items in the repair process at any given time.

IV. SIMULATION RESULTS AND ANALYSIS

A. OVERVIEW

This Chapter provides analysis of the results of the availability simulation. Each simulation is run 100 times. Simulation output is collected and recorded in summary reports that are provided as Appendices A through L. Summary reports are divided into three performance sections, 1) Ao, 2) AIMD, 3) Supply Department.

The first half of the Chapter focuses on the baseline simulation. The baseline simulation is constructed to replicate the ARROWs estimate of Ao. The results of the baseline are used to determine if the WRA allowances established by ARROWs yield the Ao desired. In addition to quantifying Ao, the baseline demonstrates that Ao is a random variable. As such, the variance and underlying distribution of Ao are determined.

The second half of the Chapter analyzes each of the simulation excursions. Simulation excursions examine a variety of factors not considered in ARROWs or the baseline simulation. Discussion of each excursion includes an explanation of why it was investigated and how the excursion was integrated into the baseline simulation. The results of each excursion are then compared with the results of the baseline to determine the overall impact of each excursion on the distribution of Ao.

B. ANALYSIS OF THE BASELINE SIMULATION

Appendix A provides a summary report of all baseline simulation output.

1. Characterizing the Distribution of Ao

The first stated purpose of this thesis is to demonstrate that Ao is a random variable. As such, it can be characterized with a mean value, a variance and an underlying distribution.

a. Determining the Mean Value of Ao

The baseline simulation is designed to replicate ARROWs as closely as possible. As such, the simulated Ao for each TMS should be approximately equal to the ARROWs calculated Ao as well as the ARROWs Ao target. The ARROWs calculated Ao, for each TMS, is an output of the model resulting from the Type 2 Ao calculation described in Chapter II. This value is typically very close to the TMS Ao traget which is an input to the model.

The simulated mean values of Ao are obtained by averaging the 100 observations of Ao obtained by running the baseline simulation. These values along with the ARROWs calculated and target Ao's are provided in Table 2. A graphical representation is found in Figure 1.

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Simulated Mean Ao	.604	.601	.550	.614	.630	.684	.596	.608	.698
ARROWs Calc. Ao	.602	.610	.557	.584	.638	.660	.567	.601	.662
ARROWs Target Ao	.600	.600	.560	.560	.640	.660	.560	.600	.660

Table 2. Ao by TMS

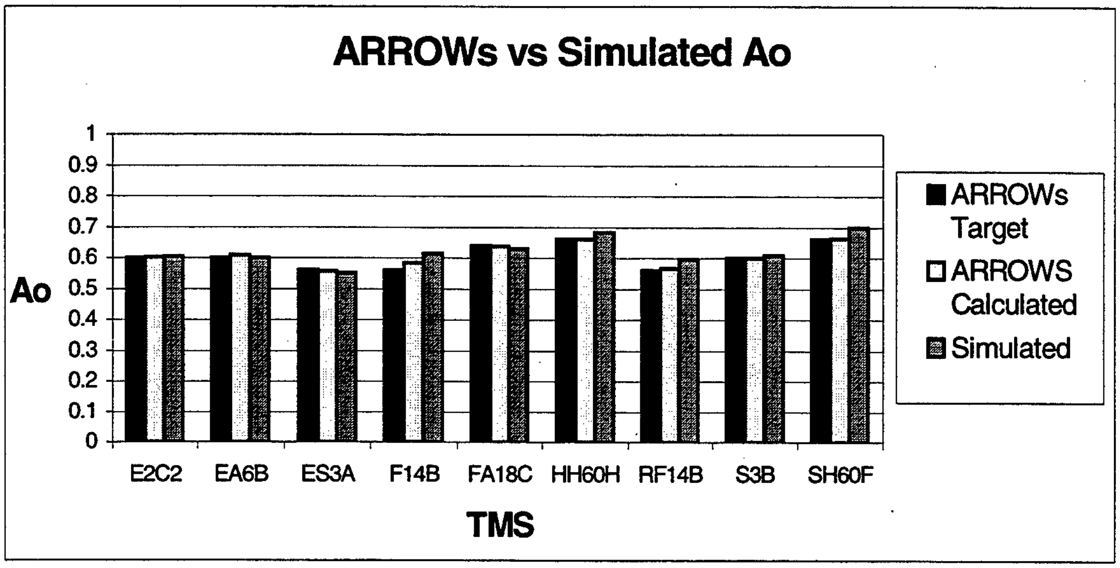

Figure 1. ARROWs vs Simulated Ao

In five of nine cases, the simulated values of Ao are approximately equal to the ARROWs calculated and target Ao. The exceptions are the F14B, RF14B, HH60H and the SH60F which have simulated availability's higher than either the ARROWs calculated or target Ao.

The average simulated Ao is only an estimate of the true simulated mean value of Ao. The Central Limit Theorem states that the distribution of the estimated mean value of a random variable is Normally distributed regardless of the random variable's underlying distribution. This allows for a more rigorous test of the hypothesis that simulated Ao = the ARROWs calculated Ao, using a Standard *Z* test. The test is conducted as follows:

Null Hypothesis (Ho): Simulated Ao = ARROWs calculated Ao

Alt. Hypothesis (Ha): Simulated Ao $\neq$ ARROWs calculated Ao

Test Statistic: $z = \dfrac{\textbf{(Simulated Ao)} - \textbf{(ARROWS Calculated Ao)}}{\hat{s}/\sqrt{n}}$,

where,

$\hat{s}$ = Standard Deviation of Sample Means;

n = Number of Samples = 100;

Critical Value: $Z = \pm 1.96$ = 95% Confidence, two sided test.

Test: If $|z| \le |Z|$, then accept Ho. Else, reject Ho.

The results of the Standard Z test are mixed. Four of the nine TMS, namely E2C2, EA6B, ES3A and S3B, pass the test and do not reject the hypothesis that simulated Ao = ARROWs calculated Ao. One TMS, FA18C, fails the test based on simulated Ao being too low to accept the hypothesis that it is equal to the ARROWs calculated Ao. The remaining TMS, F14B, RF14B, HH60H and SH60F, fail the test based on simulated Ao being too high to equal ARROWs calculated Ao.

Based on the results of the Standard Z testing, it cannot be confidently stated that the simulation and ARROWs calculated mean availability's are statistically equivalent. The specific reasons for the differences are not determined. All that can be stated is that the simulation provides a relatively accurate approximation of ARROWs with respect to Ao.

b. Determining The Variance of Mean Ao

The simulated variance of Ao is estimated, for each TMS, using the sample variance of the 100 mean values of Ao resulting from the 100 baseline simulation runs. Each individual simulation run also represents a mean value of Ao. This mean value is the Ao estimate for the population of each TMS in the carrier deckload for that

simulation run. The result is that TMS with high populations in the deckload, like FA18C and F14B, have significantly more observations of individual aircraft Ao than TMS with small populations such as ES3A and HH60H.

For example, the FA18C has 36 aircraft operating in each simulation run and 100 runs are simulated. The result is 3600 individual FA18C aircraft Ao observations. The ES3A has only two aircraft operating in each simulation run. 100 runs yields only 200 individual ES3A aircraft Ao observations.

The standard deviation for the 100 observations of mean Ao, for each TMS, is estimated empirically as follows:

$$\hat{s}_{TMS\_Ao} = \sqrt{\frac{\sum_{i=1}^{n}\left(Ao_i - \overline{Ao}\right)^2}{n-1}} \; ,$$

where,

$\hat{s}_{TMS\_Ao} \approx \sigma_{TMS\_Ao\_for\_100\_Runs}$;

n = *100 Simulation Runs*;

Ao_i = TMS Mean Ao for one run;

$\overline{Ao}$ = TMS Mean Ao for 100 runs.

This can be stated differently as

$$\hat{s}_{TMS\_Ao} \approx \sigma_{TMS\_\overline{Ao}\_for\_100\_Runs} = \frac{\sigma_{TMS\_Ao\_for\_1\_Run}}{\sqrt{100}}$$

and

$$\sigma_{TMS\_Ao\_for\_1\_Run} = \frac{\sigma_{TMS\_Ao\_for\_1\_Aircraft}}{\sqrt{TMS\_population}}.$$

Substituting the above two equations leaves

$$\sigma_{TMS\_Ao\_for\_100\_Runs} = \left(\frac{\sigma_{TMS\_Ao\_for\_1\_Aircraft}}{\sqrt{TMS\_population}}\right)\cdot\left(\frac{1}{\sqrt{100}}\right)$$

or

$$\sigma_{TMS\_Ao\_for\_100\_Runs} = \left(\frac{\sigma_{TMS\_Ao\_for\_1\_Aircraft}}{\sqrt{100}}\right)\cdot\left(\frac{1}{\sqrt{TMS\_population}}\right).$$

Setting $\left(\frac{\sigma_{TMS\_Ao\_for\_1\_Aircraft}}{\sqrt{100}}\right)$ equal to a proportionality constant k_{TMS} leaves

$$\sigma_{TMS\_Ao\_for\_100\_Runs} = k_{TMS}\cdot(TMS\_population)^{-0.5}.$$

The estimate of standard deviation for the 100 simulated mean values of TMS Ao should be inversely proportional to the square root of TMS population. An examination of TMS mean Ao standard deviation reveals that it is in fact inversely proportional to the square root of TMS population. When TMS population is relatively high, the corresponding mean Ao standard deviation is relatively low. The converse also appears true. Simulated mean Ao standard deviation and TMS populations are provided in Table 3.

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Simulated Mean Ao Std. Dev.	.080	.085	.106	.046	.029	.110	.050	.052	.110
# of aircraft	4	4	2	12	36	2	8	8	3

Table 3. Simulated Mean Ao Standard Deviation and TMS Population

Using the equations detailed above the proportionality constants k_{TMS} were solved for and are presented in Table 4.

	TMS population	k-TMS, 100 Runs
E2C2	4	0.16
EA6B	4	0.17
ES3A	2	0.15
F14B	12	0.16
FA18C	36	0.17
HH60H	2	0.16
RF14B	8	0.14
S3B	8	0.15
SH60F	3	0.19
	Average:	0.16

Table 4. Mean Ao Standard Deviation Proportionality Constants

Analysis of these constants does not reveal a strong relationship with TMS population. A relationship between these constants and the installed number of WRAs was also explored but no relationship was found. Assuming that these constants are equal for an aircraft of any TMS, then the average value serves as the best estimate of the true, unknown value. The average k_{TMS} for 100 simulation runs is 0.16. Based on the calculations above, the mean Ao standard deviation, estimated empirically, should be well modeled by the equation below.

$$\hat{s}_{TMS\_Ao} \approx (0.16) \cdot (TMS\_population)^{-0.5}$$

Non-Linear regression was used to model mean Ao standard deviation as a function of aircraft population. The following model was developed:

$$\hat{s}_{TMS\_Ao} = (0.1585) \cdot (TMS\_population)^{-0.4935} .$$

Model statistics are as follows:

F-statistic: 0.000

t-statistic: 0.000

R^2: .962

R^2_{adj}: .956

Coefficient of Variance (CV): 1.33%

The best-fit non-linear model above very accurately characterizes the relationship between mean TMS Ao standard deviation obtained from the simulation and TMS population. It is also extremely close to the model derived. In the absence of simulated data, the derived model should serve as a good estimator for the ARROWs standard deviation of mean TMS Ao.

c. Determining the Underlying Distribution of Ao

The distribution of Ao for each TMS is best characterized graphically by histograms. Histograms have observed values of the random variable being characterized along the x axis. The random variable being characterized here is Ao. The range of Ao is partitioned into bins. The y axis represents the number of times the value of Ao was observed to have occurred inside a particular bin.

The simulated Ao histograms for all nine TMSs are provided in Figure 2 through Figure 10. The range of Ao values for each histogram is 0.275 to 0.925. The range of the y axis in each histogram is zero to 40. Like scaling of all nine histograms

allows meaningful comparison from one histogram to the next. The relative variability of Ao from TMS to TMS is clearly evident. The ARROWs Ao target is identified on each histogram by a bold vertical line. Examination of the Ao histograms clearly indicates how little information about the actual "likely to be realized" Ao is conveyed by the point estimate of Ao made by ARROWs.

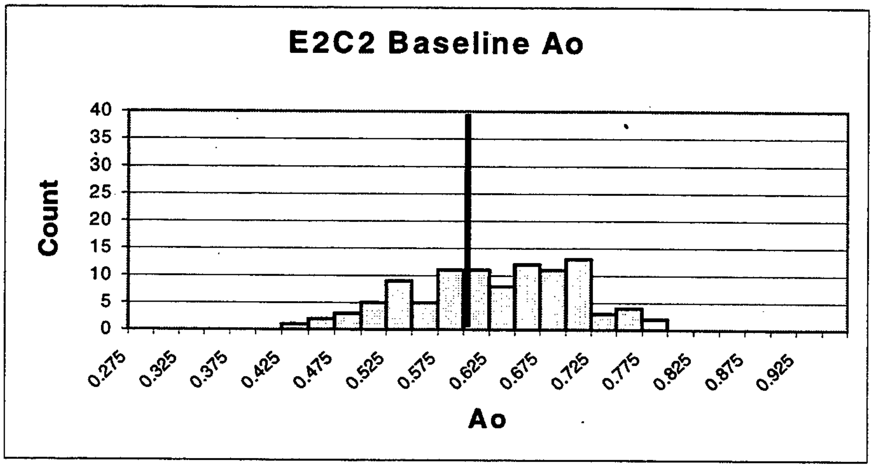

Figure 2. Histogram of E2C2 Baseline Ao

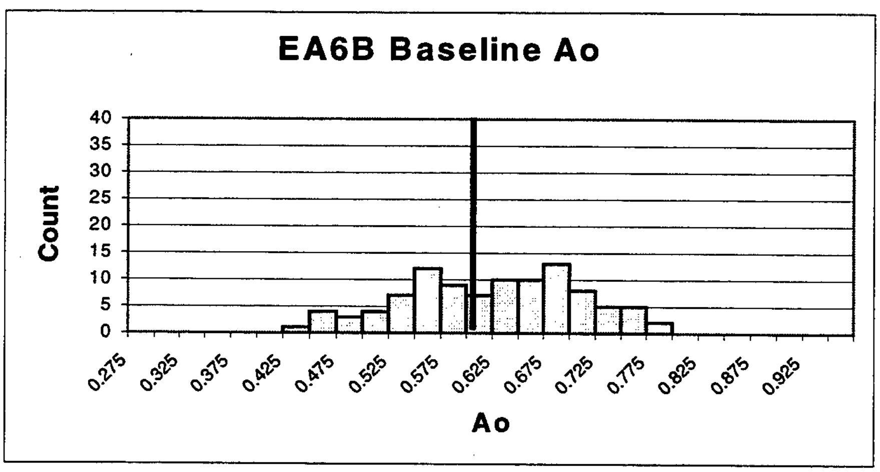

Figure 3. Histogram of EA6B Baseline Ao

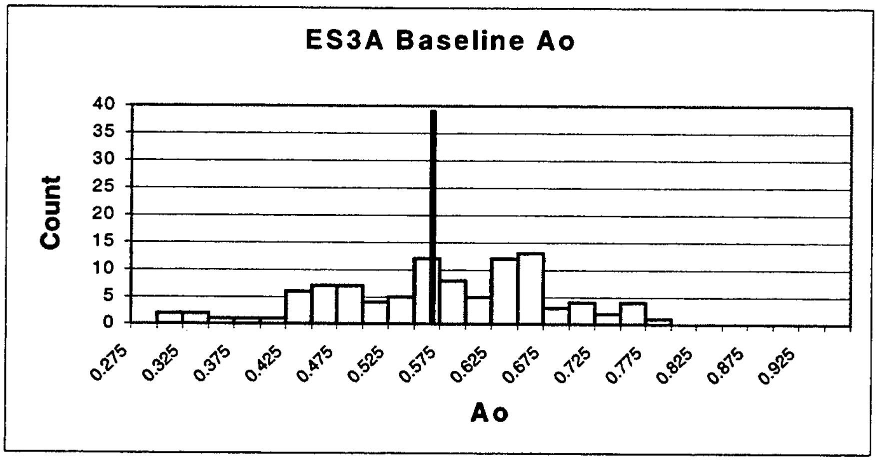

Figure 4. Histogram of ES3A Baseline Ao

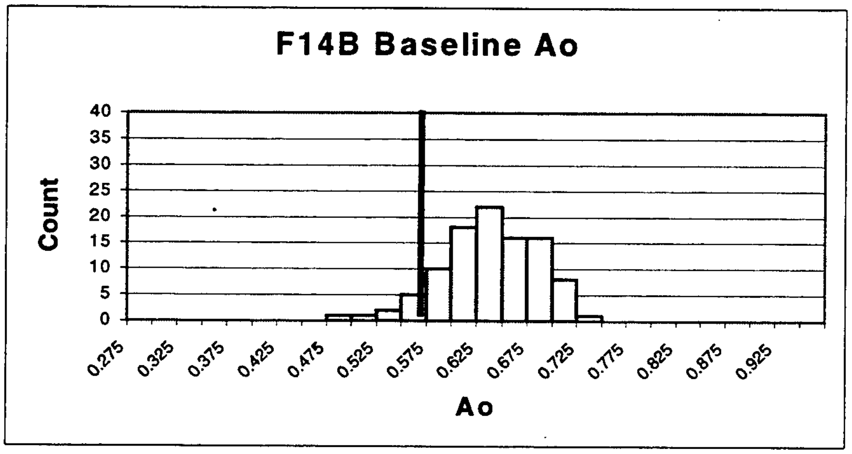

Figure 5. Histogram of F14B Baseline Ao

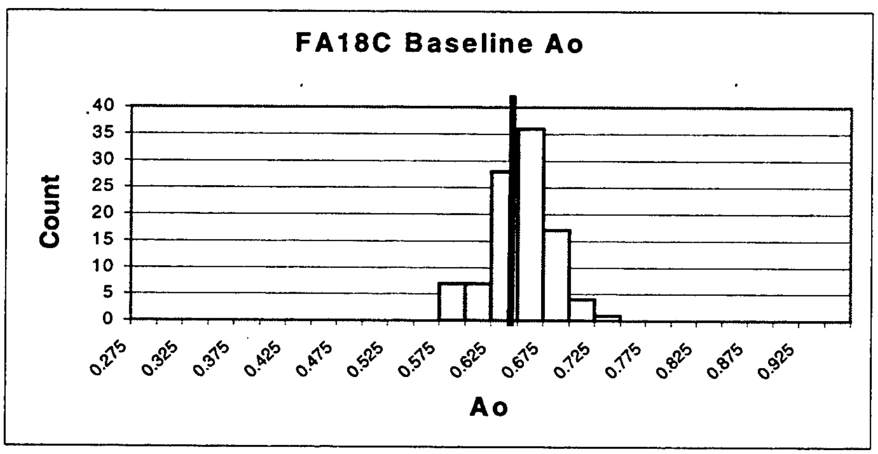

Figure 6. Histogram of FA18C Baseline Ao

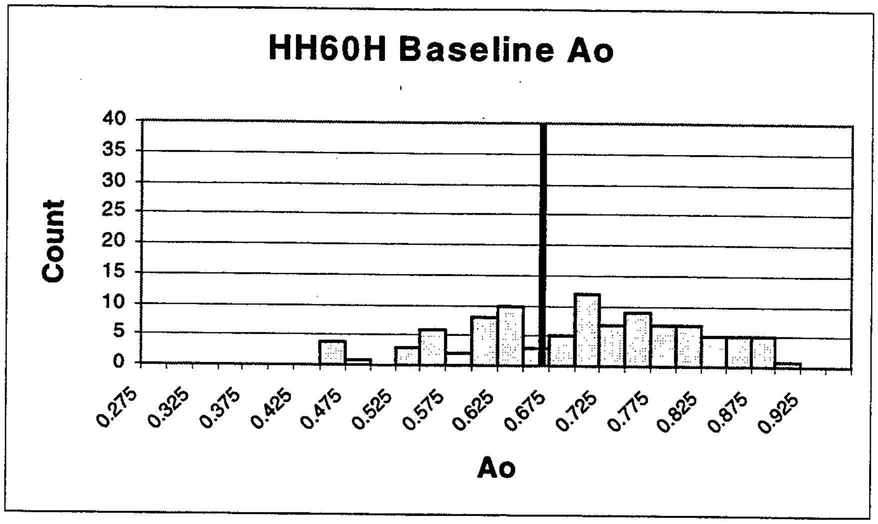

Figure 7. Histogram of HH60H Baseline Ao

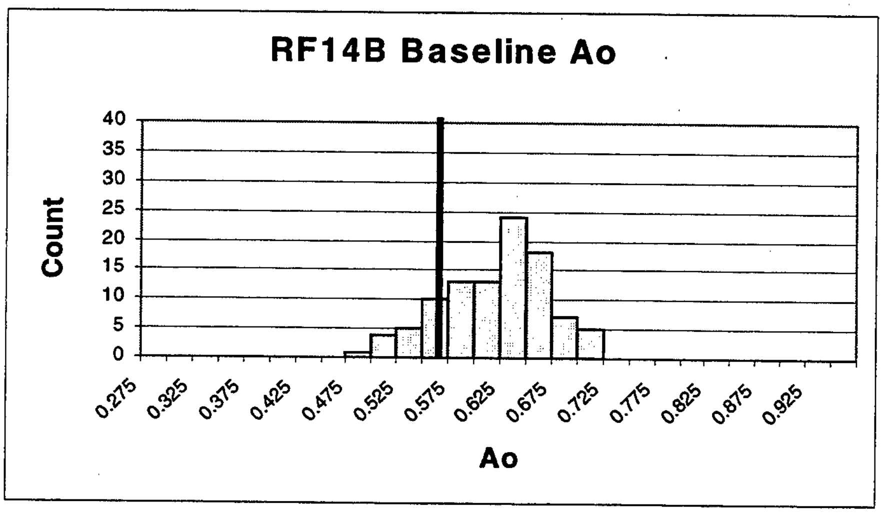

Figure 8. Histogram of RF14B Baseline Ao

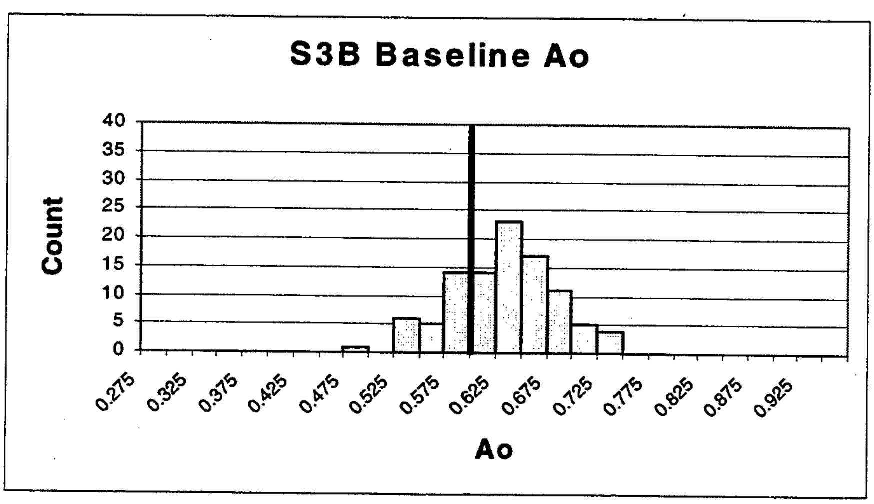

Figure 9. Histogram of S3B Baseline Ao

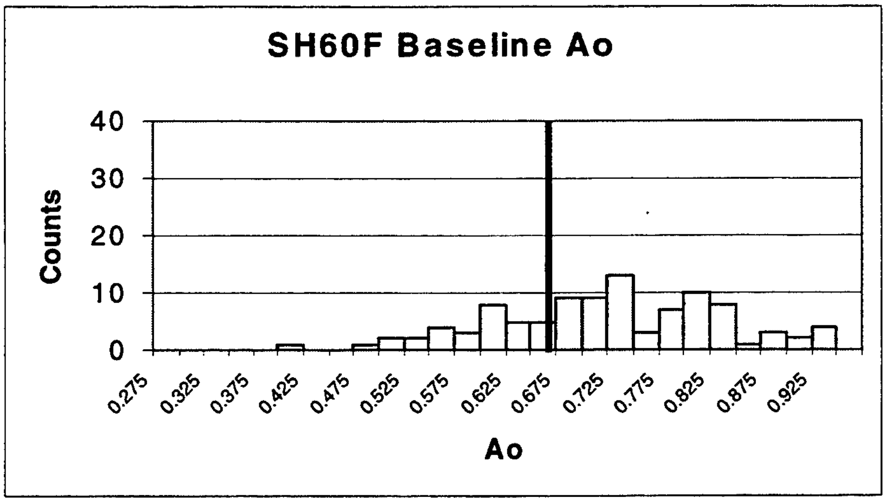

Figure 10. Histogram of SH60F Baseline Ao

The histograms reveal that Ao for all TMSs is relatively symmetric and most are centered near the ARROWs target Ao. As stated in Chapter II, each aircraft is represented by a series system. The individual WRAs in the TMS configuration are the series elements and the TMS Ao can be calculated as the product of the individual WRA availabilities, a_{oi}.

$$A_o = \prod_{i=1}^{n} a_{o_i}$$

ARROWs obtains TMS Ao by calculating each of the a_{oi}'s and computing their product. The simulation does not calculate individual a_{oi}'s but it does model aircraft as a series system. Each WRA is required to be functioning for the aircraft to function. The simulation directly observes the value of Ao achieved rather than computing its value as does ARROWs. The result is that TMS Ao, although determined differently by ARROWs and the simulation, is the result of a series system.

The Central Limit Theorem states that if the random variables x_i are positive and independent and the random variable Y is the product of those random

variables then the distribution of Y is approximately Lognormal when the number of x_is, n, is large [Ref. 11: p. 231].

$$Y = \prod_{i=1}^{n} x_i \approx Lognormal(y, \mu, \sigma)$$

The random variable Y in this analysis is the Ao for a specific Type Model Series (TMS) aircraft. The random variables x_i, are the a_{oi}'s of the individual WRAs that make up the TMS configuration. The number of WRAs/TMS, n, is sufficiently large for all TMS. It follows that TMS Ao is approximately Lognormally distributed with the following Probability Density Function (PDF):

$$f(Ao, \mu, \sigma) = \frac{1}{\sqrt{2 \cdot \pi}(\sigma \cdot Ao)} e^{-\frac{(\ln(Ao)-\mu)^2}{2\sigma^2}} \{Ao \geq 0\} ,$$

where, μ and σ are not equal to mean and standard deviation (SD) of Ao, but rather μ and σ equal mean and SD of ln(Ao).

The mean and variance of Ao are

$$E[Ao] = e^{\left(\mu + \sigma^2/2\right)}$$

and

$$Var[Ao] = e^{(2 \cdot \mu + \sigma^2)} \cdot (e^{\sigma^2} - 1) .$$

Estimates for the E[Ao] and the Var[Ao] are available from the simulation and are denoted Ao_{SIM} and Var_{SIM} respectively. μ and σ, for each TMS can be determined as follows:

$$Ao_{SIM} = e^{\left(\mu + \sigma^2/2\right)}$$

and

$$\ln(Ao_{SIM}) = \mu + \frac{\sigma^2}{2} .$$

Therefore, $\mu = \ln(Ao_{SIM}) - \frac{\sigma^2}{2}$ (1)

and $$Var_{SIM} = e^{(2 \cdot \mu + \sigma^2)} \cdot (e^{\sigma^2} - 1) .$$

Substituting, $\mu = \ln(Ao_{SIM}) - \frac{\sigma^2}{2}$

leaves, $$Var_{SIM} = e^{\left(2 \cdot (\ln(Ao_{SIM}) - \frac{\sigma^2}{2}) + \sigma^2\right)} \cdot (e^{\sigma^2} - 1)$$

$$Var_{SIM} = Ao_{SIM}^2 \cdot e^{(-\sigma^2 + \sigma^2)} \cdot (e^{\sigma^2} - 1)$$

$$Var_{SIM} = Ao_{SIM}^2 \cdot (e^{\sigma^2} - 1)$$

$$\frac{Var_{SIM}}{Ao_{SIM}^2} + 1 = e^{\sigma^2} .$$

Therefore, $\sigma^2 = \ln(\frac{Var_{SIM}}{Ao_{SIM}^2} + 1)$. (2)

Using equations (1) and (2) derived above, the applicable μ and σ can be calculated for each TMS.

Quantile-quantile plots, or qqplots, are used to test whether the simulated values of TMS Ao do indeed fit a Lognormal(μ , σ) distribution [Ref. 12:p. 13]. 1000 random variables are generated from the Lognormal(μ , σ) for each TMS. A qqplot is then produced for each TMS using the 100 values of Ao, observed by the simulation, and the appropriate 1000 random variables produced from the Lognormal(μ , σ). If the

observed values of Ao are truly Lognormally distributed, the qqplot should result in a straight line. The qqplots for the FA18C and the ES3A are provided in Figure 11.

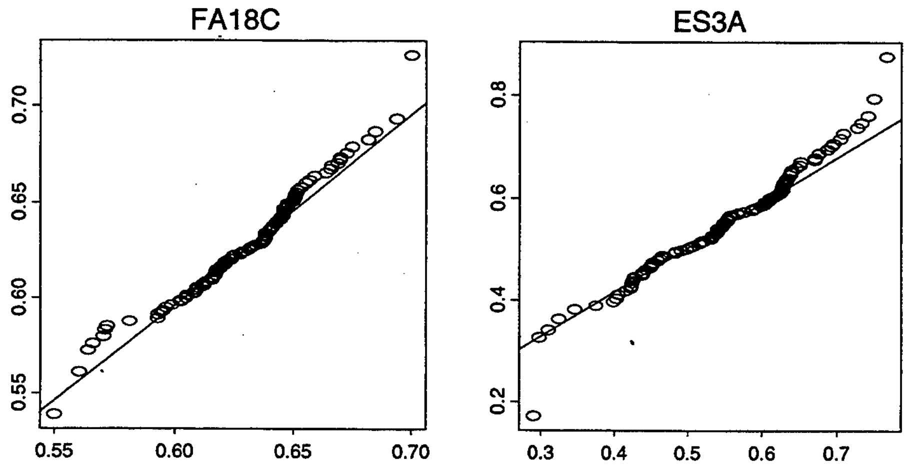

Figure 11. FA18C and ES3A Quantile-Quantile Plots

The results of qqplot testing for all TMS are well characterized by these two plots. Plots for the FA18C, S3B, F14B and SH60F closely conform to the Lognormal distribution across the entire range of Ao. The qqplots for ES3A, E2C2, EA6B, HH60H and RF14B largely conform to the Lognormal distribution but have noticeably heavier right tails. Overall, the Lognormal distribution serves as a good approximation for the distribution of simulated TMS Ao and should therefore serve as a good approximation of the distribution of the ARROWs Ao calculation.

d. Determining Confidence Intervals for Mean Ao

Because the underlying distribution of Ao has been characterized, it is now possible for confidence intervals to be determined. Upper and lower confidence limits for the mean value of a Lognormally distributed random variable, based on a sample of size n, are obtained as follows [Ref 13]:

$$lower_{TMS} = \bar{A}o_{TMS} - \left(\frac{z_{1-\alpha/2}}{\sqrt{n}}\right)\cdot\left(\sqrt{\frac{ssAo_{TMS}}{\chi^2_{1-\alpha/2}}}\right) + \frac{1}{2}\cdot\left(\frac{ssAo_{TMS}}{\chi^2_{1-\alpha/2}}\right)$$

$$upper_{TMS} = \bar{A}o_{TMS} + \left(\frac{z_{1-\alpha/2}}{\sqrt{n}}\right)\cdot\left(\sqrt{\frac{ssAo_{TMS}}{\chi^2_{1-\alpha/2}}}\right) + \frac{1}{2}\cdot\left(\frac{ssAo_{TMS}}{\chi^2_{1-\alpha/2}}\right)$$

where,

n = 100;

$\bar{A}o_{TMS}$ = simulated Mean TMS Ao;

$ssAo_{TMS}$ = the sum of squares of the observations of TMS Ao defined as $\sum_{i=1}^{n}\left(Ao_i - \bar{A}o\right)^2$;

α = .05 (95% two sided confidence interval);

$z_{1-\alpha/2}$ = critical value, standard Normal distribution ($Z_{.975}$ = 1.96);

$\chi^2_{1-\alpha/2}$ = critical value, Chi Square dist., n-1 degrees of freedom ($\chi^2_{99,.975}$ = 128.42).

Table 5. provides the 95% upper and lower confidence limits for mean Ao, for each TMS and the calculated ARROWs Ao.

TMS	Sim Mean Ao	Lower 95% Confidence Limit	Upper 95% Confidence Limit	ARROWs Calculated Ao
E2C2	.604	.593	.621	.602
EA6B	.601	.589	.618	.610
ES3A	.550	.536	.572	.557
F14B	.614	.607	.622	.584
FA18C	.630	.625	.635	.638
HH60H	.684	.670	.708	.660
RF14B	.596	.589	.606	.567
S3B	.608	.600	.618	.601
SH60F	.698	.684	.722	.662

Table 5. Confidence Intervals for Simulated Mean Ao

Examination of the confidence intervals indicates that ARROWs calculated Ao is included in the simulated mean Ao confidence bands for four of the nine TMSs. These TMSs include the E2C2, EA6B, ES3A and the S3B. These are the same four TMS that passed the standard Z test for simulated mean Ao equals the ARROWs calculated Ao. One ARROWs calculated Ao, FA18C, is higher than the upper confidence limit for simulated mean Ao. The remaining four ARROWs calculated TMS Ao's, F14B, RF14B, HH60H and the SH60F, are located outside the lower confidence limit for simulated mean Ao. Again, this replicates the results of the standard Z test for equal mean Ao estimates.

2. Conclusions regarding the Distribution of Ao

ARROWs provides a point estimate for the TMS Ao obtained by a specific WRA allowance list. The baseline model has, through simulation, partially validated those mean values. Validation is not exact for five TMS which have slightly different mean Ao than that calculated by ARROWs. The differences noted are small.

Further, the baseline simulation has shown that Ao is a random variable. The variance of Ao can be approximated by the following equation:

$$\hat{s}_{ARROWs\_TMS\_Ao} \approx (0.16) \cdot (TMS\_population)^{-0.5} .$$

Analysis of the distribution of Ao reveals it is closely approximated by the Lognormal(μ, σ). The parameters μ and σ, can be determined based on the simulated mean Ao and the simulated standard deviation of mean Ao using the equations below.

$$\mu \approx \ln(Simulated\_\overline{A}o) - \frac{\sigma^2}{2}$$

$$\sigma \approx \sqrt{\ln\left(\frac{(Std\_Dev\_\overline{A}o)^2}{(Simulated\_\overline{A}o)^2}+1\right)}$$

In the absence of simulated data, the ARROWs calculated Ao and the approximation for standard deviation of mean Ao, based on TMS population, can be used to approximate μ and σ. This provides planners and decision-makers considerably more data about the expected value of TMS Ao than was previously available.

3. Comparison of ARROWs and Simulated Supply Department Effectiveness

ARROWs output reports provide expected values for net and gross supply effectiveness by Cognizance Symbol (Cog). These figures can be algebraically manipulated to obtain overall WRA net and gross supply effectiveness for comparison to the simulated values of these same performance measures. Table 6 provides the ARROWs and simulated values for a variety of supply performance measures.

	ARROWs	Sim Mean	Sim Min	Sim Max
Demands	8393	8284.6	8053	8567
Issues	7198	7257.5	7073	7508
Not Carried	124	123.8	95	153
Not In Stock	1071	903.2	799	1026
Net Eff.	87.0%	88.9%	87.6%	90.0%
Gross Eff.	85.8%	87.6%	86.2%	88.8%

Table 6. ARROWs vs Simulated Supply Effectiveness

ARROWs predictions and simulated mean values are generally similar but discrepancies do exist. The most obvious discrepancy between the ARROWs and simulated mean values are the number of Not In Stock (NIS) demands. The ARROWs expected value of NIS demands is significantly larger than that observed by the simulation. Note that the maximum number of NIS demands observed in 100 runs of the

baseline simulation is less than the expected number of NIS demands computed by ARROWs. The discrepancy in NIS demands creates a corresponding discrepancy in Net and Gross Supply effectiveness.

The reason for the discrepancy in NIS demands is not known. It is highly probable that this discrepancy is linked in some manner to the simulation producing higher Ao values for four TMSs than those calculated by ARROWs. The applicable TMSs are F14B, RF14B, HH60H and SH60F. These aircraft have a high percentage of like WRAs. That is to say they have very similar configurations because they are variants of the same aircraft. The ARROWs documentation is not rigorous in its description of how WRAs, common to multiple TMS, are handled in the model. It is suspected that the handling of shared WRAs by ARROWs and the simulation may be different resulting in the observed discrepancies. Detracting from this notion is the fact that the ES3A and S3B also have a high percentage of like WRAs, but the simulation and ARROWs calculated values of the mean Ao are virtually identical.

Like TMS Ao, the results of direct comparisons of ARROWs and simulated Supply Department performance measures are mixed. It appears that the simulation is representative of the ARROWs model but differences do exist. These differences can be quantified but their cause cannot be accurately described. Again, these measures are random variables, and differences between simulated values and ARROWs point estimates should be expected.

C. ANALYSIS OF SIMULATION EXCURSIONS

The baseline simulation and all simulation excursions produce the same output allowing direct comparison of a variety of system performance measures. Output for all

simulation excursions and the baseline is summarized in Appendices A through L. Output is divided into three performance sections, 1) Ao, 2) AIMD and 3) Supply Department. Discussion of simulation excursions includes a brief description of why the excursion is being investigated, how it is integrated into the baseline model and significant differences between the excursion and the baseline simulation.

1. Case 1, Analysis of 180 Day Support Period

The baseline simulation models the performance of a set of WRA allowances in supporting the air-wing for an operating period of 90 days. Actual carrier deployments are twice that duration or 180 days. This excursion quantifies the impact on Ao of operating the simulated system for 180 vice 90 days. Changes to the baseline simulation are limited to the ATO object. The number of the ATO's monthly sortie requirements matrices (as described in Chapter III, Section D) is doubled from three to six. The additional matrices are populated with the same flying hour program as the original matrices. The results of Case 1 are summarized in Appendix B. Figure 12 provides a comparison of TMS Ao observed for a 90-day support period, the simulated baseline, and the Case 1 180 day support period.

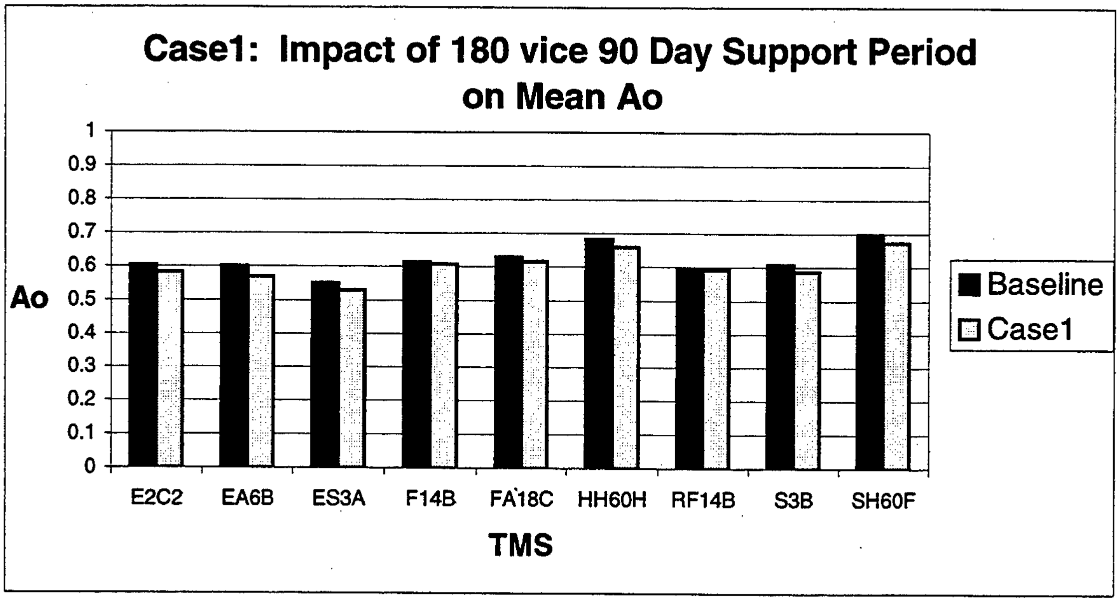

Figure 12. Case 1, Impact of 180 vice 90 Day Support Period on Mean Ao

The doubling of the support period from 90 to 180 days negatively impacts mean Ao for all TMSs. The magnitude of these decreases is relatively small averaging just 0.017 across all TMSs. Some decrease in mean Ao for a longer support period is expected. Also noteworthy is the fact that mean Ao standard deviation has decreased for all TMSs due to the increased number of simulated observations. This results in the PDF of Ao being more concentrated about the mean value. This effect is graphically displayed in Figure 13 for the F14B.

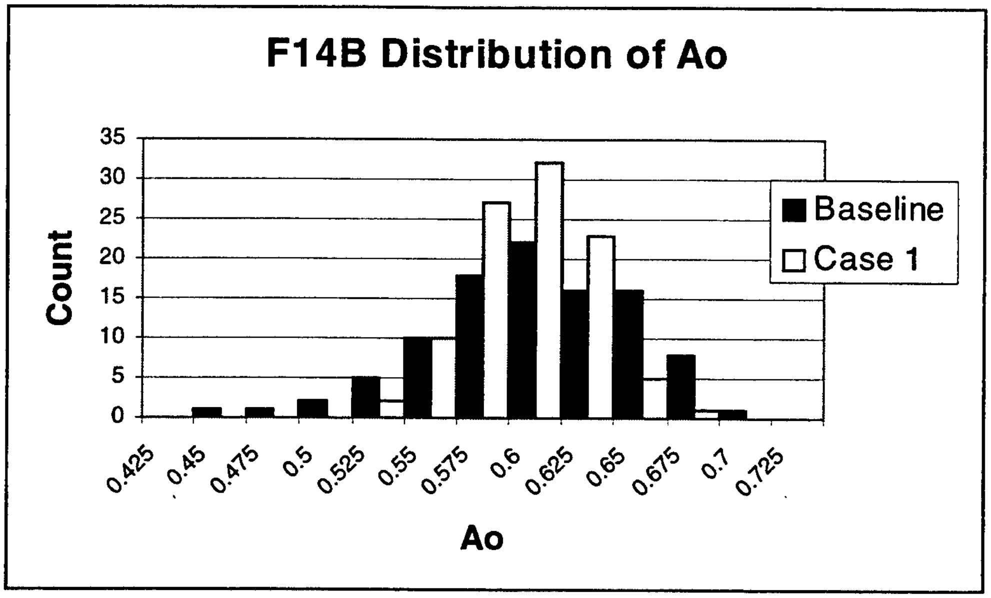

Figure 13. Case 1, F14B, Impact of 180 vice 90 Day Support Period on the Distribution of Ao

Examination of Supply Department and AIMD performance measures (see Appendix B) reveals no significant changes from the baseline simulation. A very slight increase in the percentage of NIS demands results in a slight decrease in Net and Gross Effectiveness resulting in the observed decrease in mean Ao.

Overall, the ARROWs WRA allowances appear to provide a relatively consistent level of support for a typical aircraft carrier deployment period of 180 days. Doubling the support period is expected to have some negative impact on Ao based on a fixed allowance of spare WRAs. An average decrease in mean Ao of 0.017 for all TMSs is noted.

2. Case 2, Analysis of Actual Vice Notional Flight Schedule

The actual flying hour program, executed by the USS GEORGE WASHINTON air-wing, differs significantly from the notional flying hour program developed for the

baseline simulation. The notional flying hour program uses a wartime flying hour program and distributes those flight hours as evenly as possible across the 90 day period. The actual flying hour program is different in three major ways. First, total flying hours required are significantly less than the wartime requirement; second, flight hours are not evenly distributed from day to day; and third, average TMS sortie durations are not two hours.

The impact of these scheduling changes on Ao is quantified by changing the ATO object's sortie requirements matrix to reflect the actual vice notional sortie requirements. The quantity and day to day distribution of actual sortie requirements is available from the Aviation Material Readiness Reports (AMRRs) filed by the USS GEORGE WASHINGTON's air-wing while deployed. The middle 90 days of this data is used to develop actual sortie requirements for use by the ATO object. Use of 90 days of deployment data allows direct comparison with the baseline simulation. The middle 90 days were selected to exclude beginning and end of deployment aberrations in the flight schedule. Average sortie duration for each TMS is also computed using the data available in the AMRR. These observed sortie durations are substituted into the air-wing object for the previously assumed values of two hours. The complete results of Case 2 can be found in Appendix C. Figure 14 compares the observed mean TMS Ao achieved by the baseline simulation and Case 2.

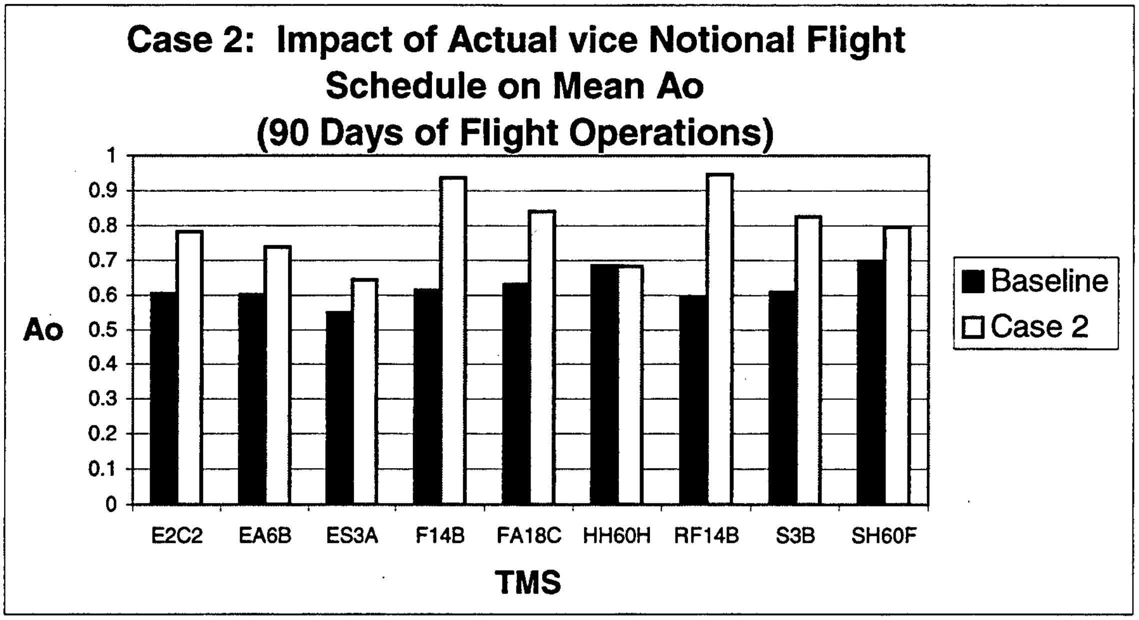

Figure 14. Case 2, Impact of Actual vice Notional Flight Schedule on Mean Ao

The use of actual flight schedule data significantly improves mean Ao for the majority of TMS. The average mean Ao improvement across all TMS is 0.178. The standard deviation of TMS mean Ao is consistently reduced and the minimum observed values of TMS Ao are significantly increased. This impact is expected due to the lower peacetime flying hour requirements. The exception is the HH60H which flew slightly more flight hours than the war-time requirement. HH60H mean Ao was virtually unchanged from the baseline. Table 7 provides a direct comparison of the total flight hours modeled in the baseline simulation and Case 2.

	War Time Notional (90 Days)	Peace Time Actual (90 Days)
E2C2	1000	728.2
EA6B	900	692.5
ES3A	600	586.6
F14B	2700	970.3
FA18C	7500	4396.7
HH60H	600	646.3
RF14B	1800	579.7
S3B	2100	1280.9
SH60F	900	719.4

Table 7. Wartime Notional and Peacetime Actual Flight Hours

To ensure the USS GEORGE WASHINGTON's flight schedule is representative of typical carrier peacetime flight schedules, it is compared to the flight schedules of four other carrier air-wings. The results of that comparison are presented in Figure 15.

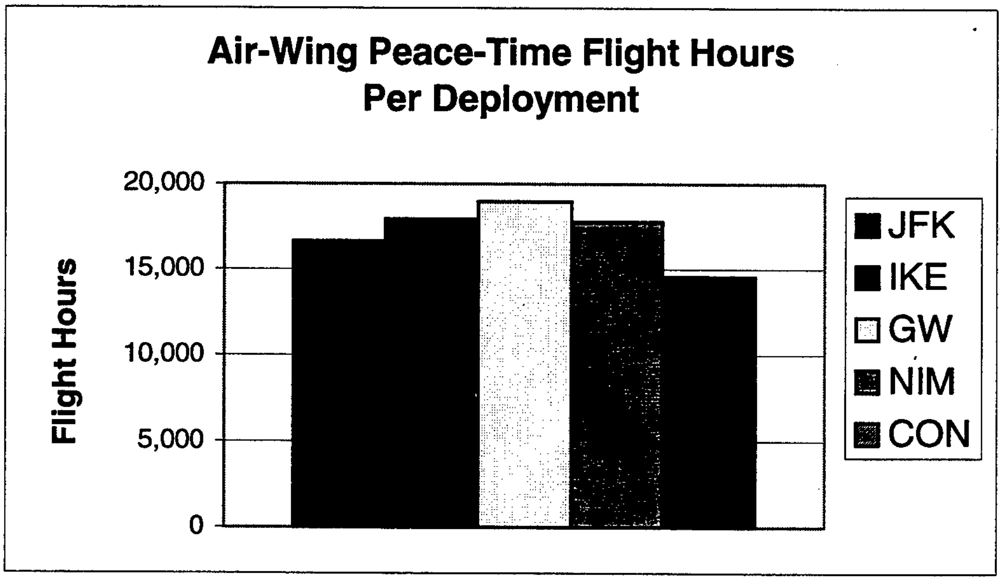

Figure 15. Air-Wing Peacetime Flight Hours Per Deployment

Figure 15 demonstrates that the USS GEORGE WASHINGTON's peacetime flying hour program is typical of deployed carrier air-wings.

Examination of Supply Department and AIMD performance measures (see Appendix C) reveals a significant reduction in total demands due to the reduced flying hour program. This results in much lower percentage of NIS demands explaining the increase in mean Ao. AIMD loading is also significantly reduced.

3. Case 3, Analysis of Prioritized Order and Shipping Time (OST)

The baseline simulation assumes an OST of 20 days for both Direct Turnover (DTO) and stock replenishment requisitions. This assumption fails to capture the fact that the OST for DTO (hi-priority) requisitions is considerably shorter than the OST for stock replenishment (routine priority) requisitions. Use of a 20-day OST for both routine and hi-priority requisitions is dictated by ARROW's inability to use differing values for these parameters.

Analysts at the Naval Inventory Control Point (NAVICP) believe more realistic estimates of mean OST are 9 days for hi-priority requisitions and 27 days for routine requisitions [Ref 14]. The impact of these differing OST's on Ao can be examined by substituting these estimates of OST for the appropriate time parameter values located in the Supply Dept. object. Appendix D provides a summary of the results of Case 3. Figure 16 compares the achieved mean Ao for this excursion to the baseline.

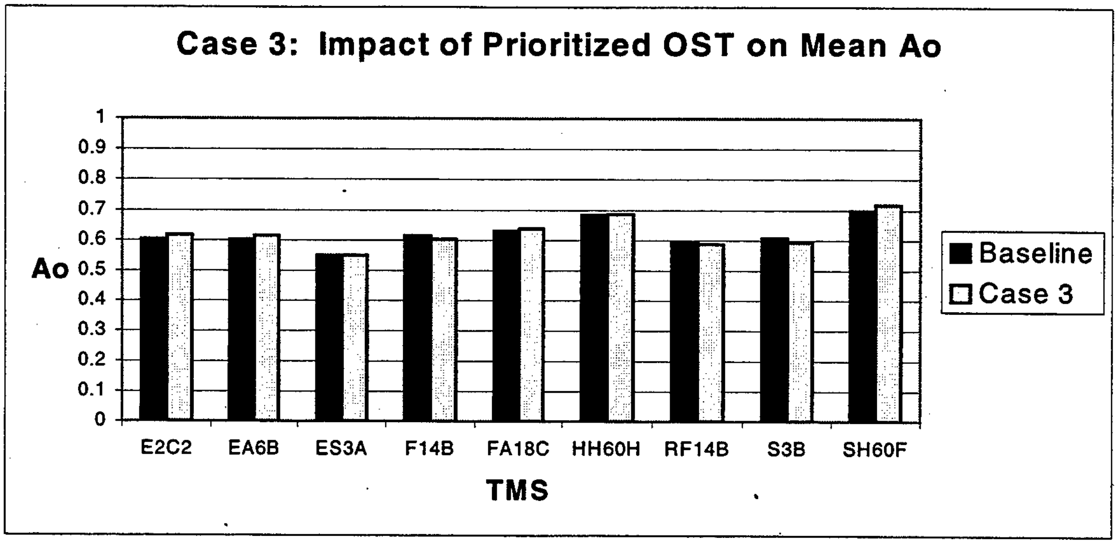

Figure 16. Case 3, Impact of Prioritized OST on Mean Ao

The impact of prioritized OST on mean TMS mean Ao is seemingly negligible. The benefits of hi-priority material arriving at the carrier, quickly, are largely offset by stock replenishment arriving more slowly. This is true for mean Ao but a closer examination of TMS Ao (see Appendix D) reveals some benefits from prioritized OST. Prioritized OST reduces the variability of mean Ao for seven of nine TMSs and increases the minimum Ao observed in six of nine TMSs. The magnitude of these improvements is relatively small.

The explanation for why prioritized OST has so subtle an impact on Ao is found in the percentage of total demands impacted by hi-priority OST. On average, approximately 87% of all WRA demands are satisfied with a storeroom issue. This is true for both the baseline and Case 3. Note that the increase in routine-priority OST from 20 to 27 days is not large enough to significantly impact supply effectiveness.

Of the remaining 13% of demands, the majority, 87%, are satisfied by an AIMD EXREP repair action. This results in only 1.2% of total demands being satisfied by a hi-

priority off-ship requisition. The impact is further reduced by the fact that almost 60% of these demands will be satisfied prior to receipt of the hi-priority requisition by a stock diversion. The end result is that only about 41 WRA demands per 90 days (or about .5% of total WRA demands) are impacted by changes to hi-priority OST. This phenomenon is further explored in Case 4, Variable OST.

4. Case 4, Analysis of Prioritized, Variable OST

OST is a random variable not a fixed value. As such, obtaining values for OST is most appropriately accomplished by sampling from a distribution. The Center for Naval Analysis (CNA) has researched the distribution of OST for hi-priority and routine priority, aviation related, deployed aircraft carrier generated requisitions. The results of this analysis were presented in a brief to NAVICP [Ref 15].

The analysis independently examined the observed OSTs of two aircraft carriers. Based on histograms of the observed data, OST is assumed exponentially distributed and Maximum Likelihood Estimation (MLE) is used to determine the distribution parameter, θ (θ = mean). The results of this analysis reveal mean values of 41 and 36 days for routine OST and 34 and 22 days for priority OST. The notion that OST can be characterized by an exponential distribution is widely accepted, but the MLE estimates of mean value are believed by NAVICP to be higher than actual. This belief is based on the possible inclusion of non-aviation requisitions in the data analyzed [Ref. 16]. Analysis by CNA and NAVICP into this subject is ongoing.

Examining the impact of variable OST on this simulation and the resulting TMS availability is desired. In the absence of a better distribution, and based on the CNA study previously mentioned, the exponential distribution is used. The mean values for

the distribution of high and routine priority OST are debatable so three sub-cases are simulated.

- Case 4a: In this case, an expected value of 20 days for both routine and hi-priority requisitions is utilized. These mean values are the same values as the point estimates used in the baseline simulation allowing the impact of OST variability to be isolated.
- Case 4b: This case uses an expected value of nine days for hi-priority OST and 27 days for routine priority OST. These are the point estimates recommended by NAVICP and simulated in Case 3. Once again, this allows direct comparison to a simulation with the same expected values but no variability.
- Case 4c: This case uses the MLE estimates determined in the CNA OST analysis. Although these estimates may be high, they are based on actual observed OST data. The more optimistic of the two models developed is selected. The mean OSTs are 22 days for hi-priority requisitions and 36 days for routine priority requisitions.

Incorporation of variable OST in the simulation requires modification of the Supply Dept. object. When requisitions are generated, the Supply Dept. assigns an OST. Instead of assigning the point estimate used in the baseline or Case 3 scenarios, a sample is drawn from an exponential distribution with the appropriate mean value. To preclude unrealistically short OSTs, the exponential distributions are shifted by 4 days. For example, the mean value for hi-priority OST in Case 4a is 20 days. This is modeled as OST = 4 + Exp(16) where mean = θ = 16. The expected value equals 20 days, but

receipt prior to 4 days is precluded. The results of Cases 4a, 4b and 4c are summarized in Appendixes E, F and G, respectively. The impact of variable OST on mean TMS Ao is provided in Figure 17.

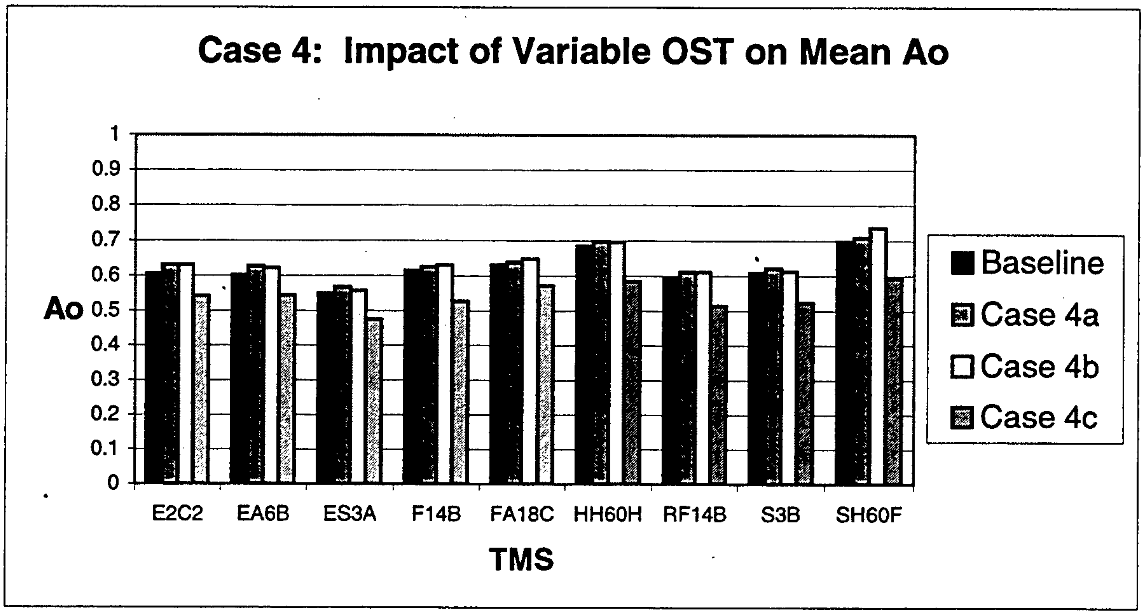

Figure 17. Case 4, Impact of Variable OST on Mean Ao

The impact of Cases 4a and 4b on Ao are largely negligible. The magnitude and variance of the changes to OST, both hi-priority and routine-priority are not significant enough to change the performance of the overall system.

In Case 4c however, changes in OST magnitude and variance are significant and have had a corresponding impact on the system as a whole. Average decrease in mean Ao across all TMSs in Case 4c is 0.08. Figures 18 and 19 show that in addition to decreasing mean Ao, Case 4c has significantly increased system variability resulting in lowered minimum observed values of Ao for all TMSs.

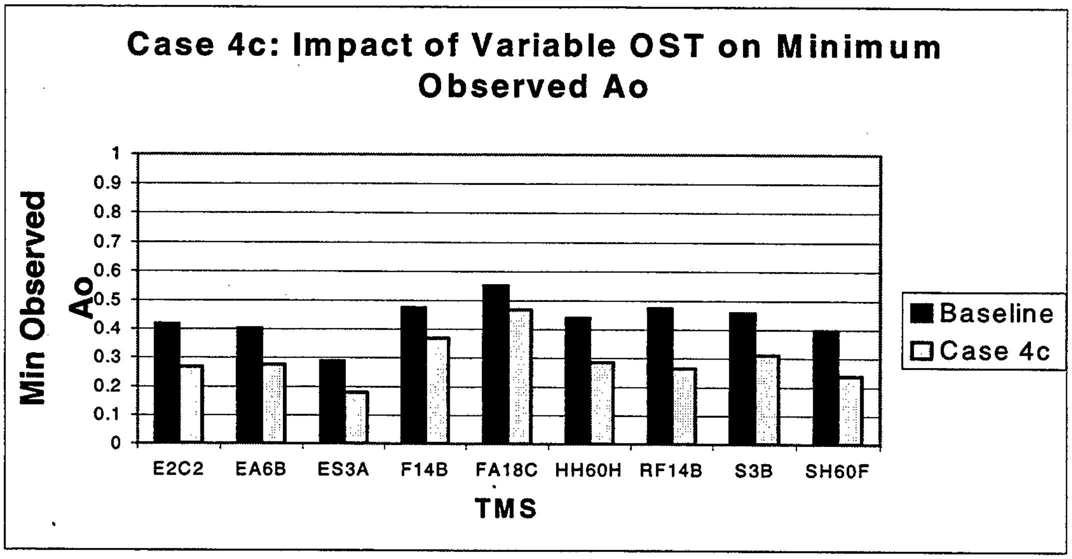

Figure 18. Case 4c, Impact of Variable OST on Minimum Observed Ao

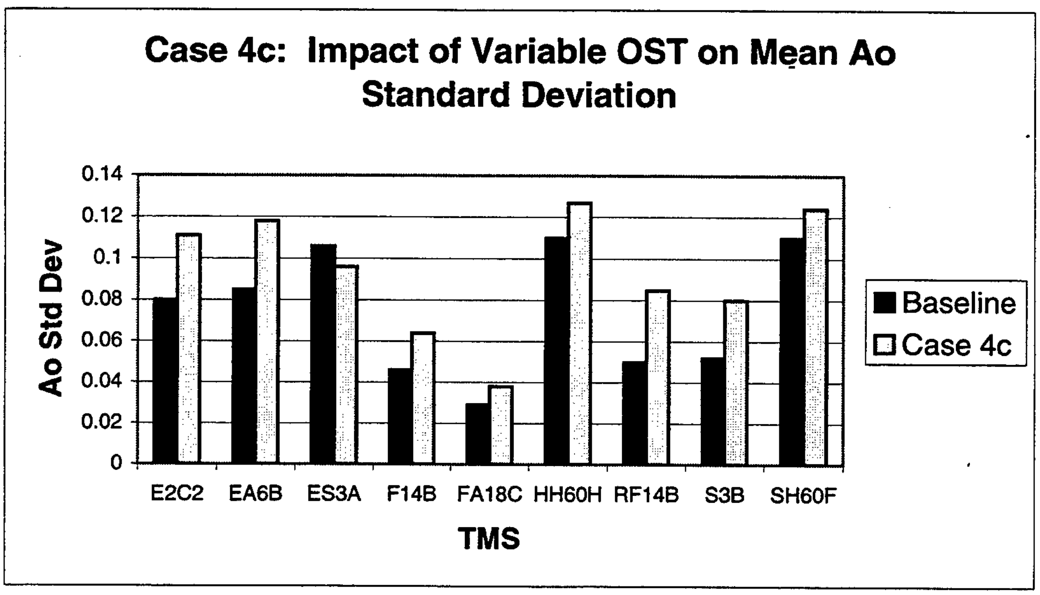

Figure 19. Case 4c, Impact of Variable OST on Mean Ao Standard Deviation

Case 4c obtains hi-priority OST values by sampling from a shifted exponential distribution with expected value equal to 22 days. This value of OST does not represent a significant change from the baseline where OST for all requisitions is 20 days. It does however add variability to the system.

The significant change in OST comes from routine-priority OST. Case 4c obtains routine-priority OST values by sampling from a shifted exponential distribution with expected value equal to 36 days. This represents an average increase of 80% for the time required to fill storeroom deficiencies and interjects even greater variability into the system.

The significant negative impact of longer and more variable OST for stock replenishment is not evident from examining Net and Gross Supply Effectiveness. Each of these performance indicators drop only 1% from baseline levels (see Appendix G). However, this small drop in overall supply effectiveness represents a 9% increase in the number of NIS demands and an 8% increase in the number of EXREPs. The most negative impact is felt by the AIMD. In the baseline simulation 93.1% of all EXREPs are repaired by the AIMD. This represents a BCM rate of 6.9%. In case 4c the EXREP BCM rate jumps to 12.2%, a 76% increase from the baseline. This increase in EXREP BCMs results in a 91% increase in the number of off-ship, hi-priority, DTO requisitions.

The reason for this dramatic impact on the supply-maintenance system is subtle but can be explained subjectively. ARROWs assumes a fixed OST of 20 days for all requisitions. ARROWs computes WRA allowances based on this OST and information about the percentage of failures that can be repaired by the AIMD. In so doing, it is more likely to stock WRAs that have a low chance of being repaired by the AIMD. WRAs that have a high AIMD repair rate are less likely to be stocked.

As the NIS rate increases (caused by longer and more variable stock replenishment OST) the mix of WRAs being inducted into the AIMD as EXREPs changes. The universe of EXREP items now contains a greater percentage of WRAs

with low repair rates. As such, a moderate increase in the NIS rate results in significantly more EXREP BCMs. The result in Case 4c is that the number of off-ship DTO requisitions almost doubles, and Ao is negatively impacted. The overall effect is that the PDF of Ao is flattened and stretched to the left increasing the probability of low Ao. Figure 20 graphically illustrate this effect.

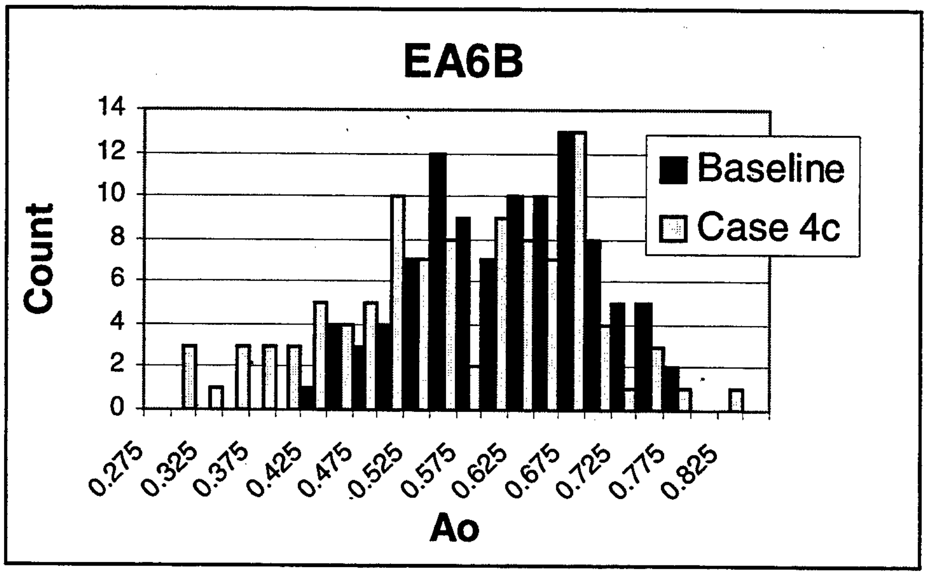

Figure 20. Case 4c, EA6B, Impact of Increased OST Variability on the Distribution of Ao

The EA6B was chosen for presentation because it most dramatically captures the stretching of the Ao PDF. Note that the maximum observed value of Ao for Case 4c is actually greater than the max value of Ao observed in the baseline. The PDF is not simply shifted but is stretched towards lower Ao. This stretching effect is the result of increased system variability. Note that the Case 4c average decrease in min Ao observed is almost 0.14 for all TMSs. The corresponding average decrease in max observed Ao is only 0.02. The probability of high Ao in Case 4c is not precluded; it is simply reduced.

5. Case 5, Analysis of Prioritized Turn Around Time (TAT)

ARROWs and the baseline simulation do not distinguish between EXREPs and stock replenishment repair actions. Both of these repair types are completed by the AIMD in one TAT. This is unrealistic in that EXREPs are completed much more quickly than stock replenishment repairs. EXREPs constitute approximately 12% (baseline simulation) of all AIMD repair activity but play a highly significant role in maintaining aircraft Ao on an actual carrier. Inclusion of this fact in the simulation and a quantification of its impact on Ao is desired.

The carrier's AIMD uses a variety of means to accelerate EXREP repairs.

- EXREPS are repaired prior to stock replenishment repairs. The AIMD functions much like a queue. Failed WRAs arrive, await service and depart. EXREPs are afforded front of the line service in this system.
- EXREPs receive first priority in the allocation of AIMD resources. This includes manpower, test equipment and repair parts.
- Material not available to complete an EXREP repair is requisitioned as hi-priority. Material requisitioned to complete stock replenishment repairs is assigned only a routine priority.

The baseline AIMD object is not designed with sufficient sophistication to capture this process as described. The simulated AIMD object completes all repairs in one TAT. However, EXREP TAT can be reduced by an improvement factor. EXREPs are typically completed in 30 to 40 percent of the time required for a stock replenishment repair [Ref. 17]. As a conservative estimate, simulated EXREP repairs are completed in one half the normal TAT. Prioritized repair using a TAT improvement factor is easily

incorporated into the simulation. The AIMD schedules EXREP repair completions in (0.5)*(TAT) vice one TAT. Complete results of Case 5 can be found in Appendix H. Figure 21 compares the mean Ao for this excursion with the baseline.

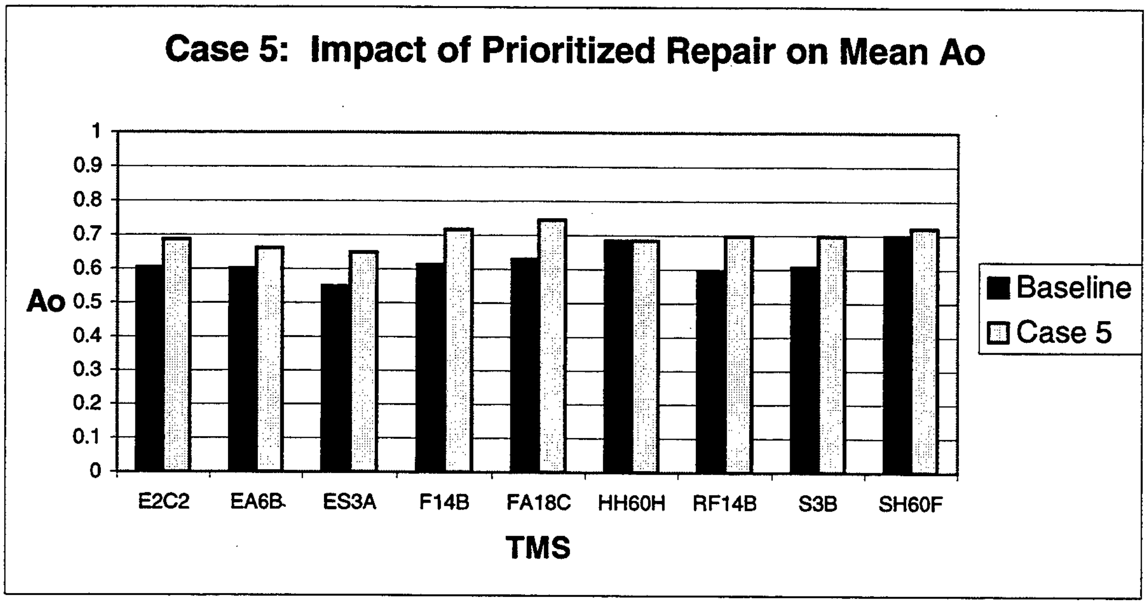

Figure 21. Case 5, Impact of Prioritized Repair on Mean Ao

The incorporation of prioritized repair has a uniformly positive and significant impact on Ao. Mean Ao is improved an average of 0.08 for all TMSs. Corresponding increases of 0.06 and 0.05 were observed for minimum and maximum values of observed Ao respectively. Standard deviation of mean Ao was reduced for seven of nine TMS, the exceptions being RF14B and SH60F (see Appendix H).

The reason for this dramatic positive impact on Ao is twofold. First, improvement in EXREP TAT impacts a large percentage of all demands not satisfied by an issue. Of all demands not satisfied by a stock issue, approximately 93% will be satisfied by an EXREP if that EXREP repair is completed quickly enough.

This point requires elaboration. In Case 5, the average number of EXREP repairs was 790 and the average number of stock diversions was 459. Stock diversions were

decreased by about 25% from the baseline quantity of 614. This reduction of 155 stock diversions represents the number of times a stock asset was not diverted to fill an EXREP requirement because the EXREP was completed more quickly. This was the intention of Case 5. In addition, some EXREPs never benefited from the diversion of stock. This number is roughly 177 and is comprised mainly of the EXREPs resulting from the 123 NC demands incurred over the support period (stock diversions are not possible for NC demands). These 177 EXREPs also correctly benefited from the prioritized TAT tested in Case 5.

The second (unintended) reason for improved Ao involves the 459 stock diversions that did occur. A percentage of these 459 stock diversions may have occurred to satisfy requirements for DTO requisitions. The average number of DTO requisitions generated in Case 5 was 70 (see Appendix H). At the time a stock repair action is completed, the simulation checks to see if a DTO requirement for this WRA exists. This requirement could be a DTO requisition or an EXREP in repair. If the WRA intended for stock can be used to prematurely satisfy a DTO requirement, off-ship requisition, or EXREP, then the simulation immediately diverts the material to satisfy the DTO requirement. Say conservatively, all 70 DTO requirements were satisfied with a stock diversion. This leaves 389 stock diversions for EXREP requirements.

The second reason for increased Ao is a significant but unintended decrease in the time required to get RFI WRAs back on Supply Department shelves. The payback WRA for each of the 389 stock diversions is an EXREP which will be repaired in half the time. In an actual AIMD, the AIMD Production Control Officer would downgrade the payback EXREP WRA to a routine repair status. The Supply Department would then wait a

routine TAT to receive its payback WRA. The simulation was not programmed to catch this subtlety. The simulated Supply Department incorrectly benefits from this error in that it receives all payback WRAs in a priority TAT. The result is an appreciable decrease in NIS demands. In Case 5, the average number of NIS demands was 756. This represents a 16% decrease from the baseline. This decrease has a significant positive impact on Ao.

It is not possible from the output available to quantify what percentage of Ao improvement is attributable to the correct application of prioritized TAT. Case 5, does however provide significant insight into the simulation and ARROWs. First, Ao is highly sensitive to changes in TAT. The 50% improvement in TAT for EXREPs modeled by Case 5 applies to only 12% of all AIMD repair actions yet has a dramatic positive impact on Ao. Second, the ARROWs allowances are well engineered. Even with a 50% reduction in TAT for EXREPs, over half of all EXREPs are still satisfied, as ARROWs intended, with an asset emerging from the repair process as a result of an earlier repair action. ARROWs has chosen allowances that do not preclude NIS demands but minimizes their impact through efficient and planned use of the AIMD.

6. Case 6, Analysis of Variable TAT

The time required to complete a WRA repair is a random variable. This random variable is estimated in ARROWs and the baseline simulation by a point estimate, Turn Around Time (TAT). TAT represents the average time to complete repairs for a given WRA. TAT is a data element in the ARROWs candidate file and is based on historic repair data.

Because TAT is a random variable, obtaining its value from a distribution is most appropriate. Obtaining values from a distribution vice using a point estimate allows the variability of the WRA repair process to be incorporated in the simulation. Case 6 incorporates this functionality. The impact of TAT variability on Ao can then be determined by comparing the results of Case 6 with those of the baseline simulation.

TAT varies significantly by WRA. ARROWs develops individual WRA allowances based on the TAT for each WRA. For this reason a general distribution for the TAT of all WRAs is inappropriate. A unique distribution for each WRA must be obtained. This is accomplished by developing empirical Cumulative Distribution Functions (CDFs) for the TAT of each WRA.

A database containing all WRA repair actions for carrier AIMDs, for calendar year 1998, was obtained from NAVICP Philadelphia. Each repair action includes the TAT in which the repair action was completed. The value of TAT is recorded in days and ranges from one to 32. TATs of greater than 32 days are extremely rare. They are reported as equal to 32 days so that they will not exert disproportionate influence on mean TAT values computed from this data. [Ref. 16]

The data is manipulated to obtain counts for the number of repairs completed in one day, two days... etc., up to the maximum TAT of 32 days. This is done for each WRA in the simulation. The result is a matrix with 3,519 rows and 32 columns. Each row corresponds to a unique WRA represented in the simulation. Columns represent the range of possible TATs, one through 32. The elements of the matrix represent the count associated with each WRA-TAT combination. Figure 22 graphically displays the contents of a single row in the matrix corresponding to an individual WRA.

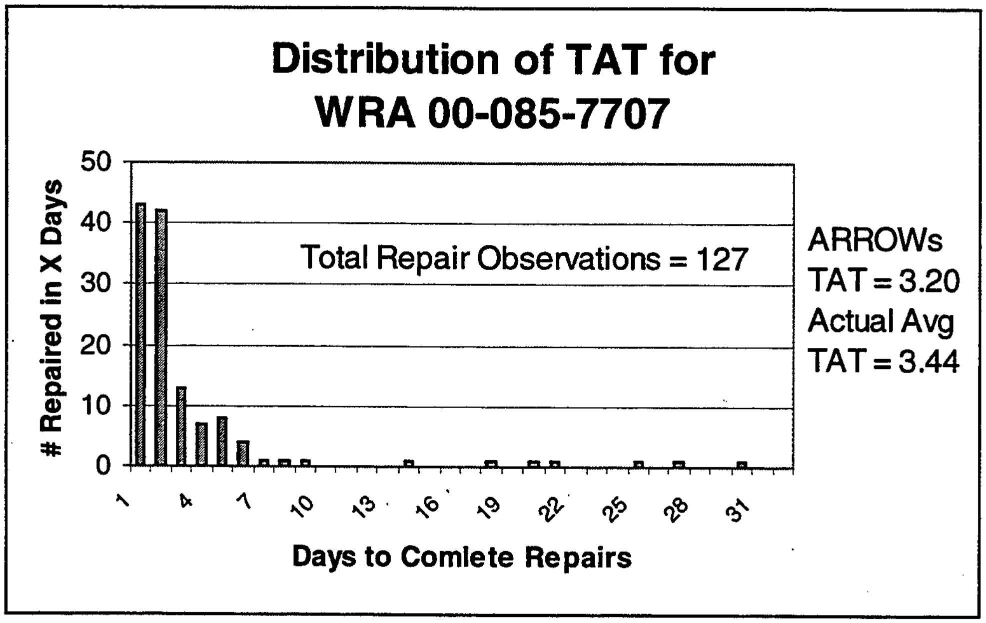

Figure 22. Distribution of TAT for WRA 00-085-7707

For this WRA, there are 127 observations of TAT. These 127 observations are distributed among the 32 possible values of TAT as indicated on the graph. Note that for this WRA, the average TAT is slightly higher than the TAT obtained from the ARROWs candidate file. This is a common occurrence.

From the contents of any row in the matrix, an empirical CDF of TAT can be constructed for the appropriate WRA. The empirical CDF for WRA 00-085-7707 is presented in Figure 23. Empirical CDFs are computed as required and are not stored by the simulation.

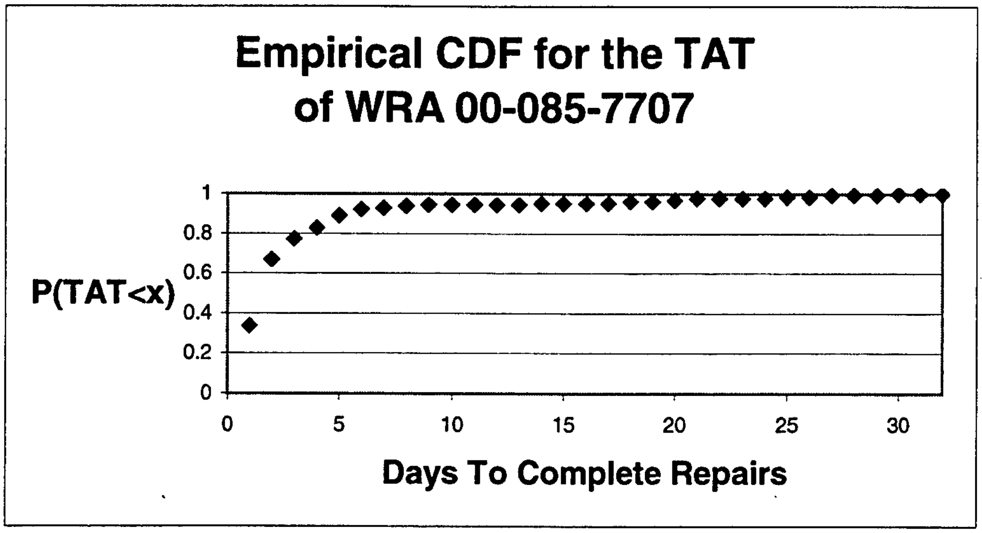

Figure 23. Empirical CDF for the TAT of WRA 00-085-7707

Variable TAT is incorporated in the simulation by embedding the matrix of TAT observations in the AIMD object. When a TAT is required by the simulation, a random variable is generated from the Uniform(0,1) distribution. The AIMD object then enters the TAT matrix at the row appropriate to the WRA being repaired with the value from the Uniform(0,1). The AIMD begins incrementing through the calculated empirical CDF from left to right until it reaches the number of days whose cumulative probability is less than the value selected from the Uniform(0,1). The point on the CDF where this occurs serves as the number of days required for this WRA repair. The AIMD schedules a repair completion at the appropriate time.

WRAs with less than 10 observations of TAT are excluded from the variable TAT calculation due to lack of data. TAT for these WRAs defaults to the point estimate for TAT used by ARROWs and the baseline simulation. This restriction applies to 3,128 of the 3,519 unique WRAs in the simulation leaving only 391 eligible for variable TAT assignment. At first glance, it appears that variable TAT will rarely be used. However

this is not the case. Only 1,322 of the 3,519 total WRAs can be repaired by the AIMD. The simulation reveals that the 391 WRAs eligible for variable TAT assignment constitute 81% of all AIMD repairs. This is judged to adequately incorporate variable TAT. Appendix I provides the summary report for Case 6. Figure 24 compares the Ao for this excursion with the baseline.

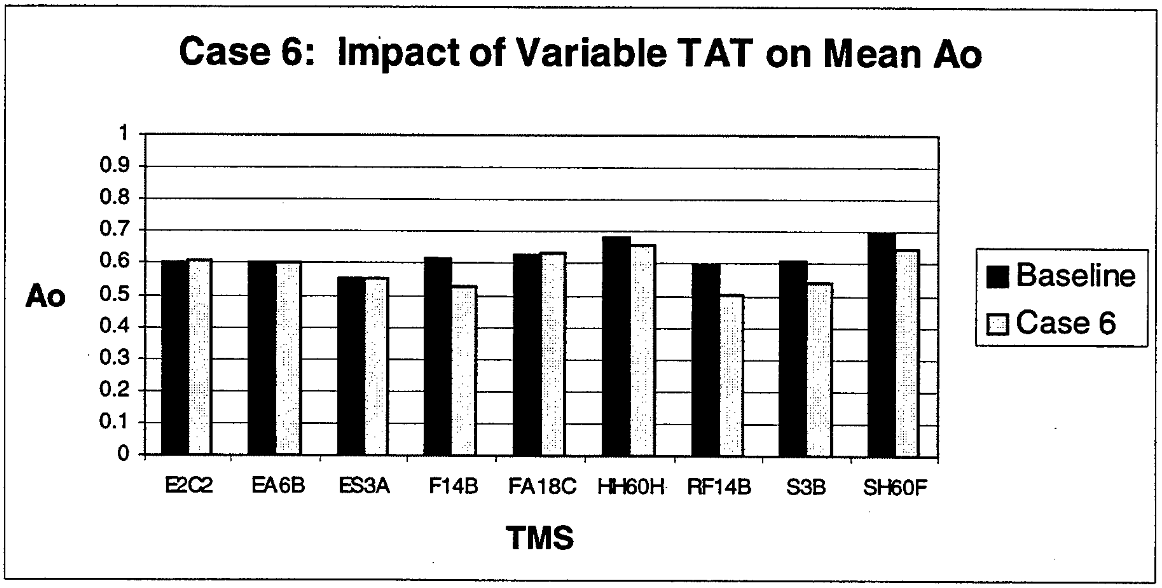

Figure 24. Impact of Variable TAT on Mean Ao

The effect of variable TAT on mean Ao is largely negative. Five of nine TMSs suffer reduced mean Ao. Mean Ao for the other four TMSs remain relatively constant. This change in mean Ao is the result of actual TAT expected values differing from those used by ARROWs and the baseline. This indicates that the values of TAT used by ARROWs may be optimistic when compared to actual repair records of TAT.

The primary focus of Case 6 is to investigate the impact of increased variability on the distribution of Ao. As expected, the introduction of TAT variability has increased the variability of mean Ao. Figure 25 graphically illustrates the increase in mean Ao standard deviation for all TMSs.

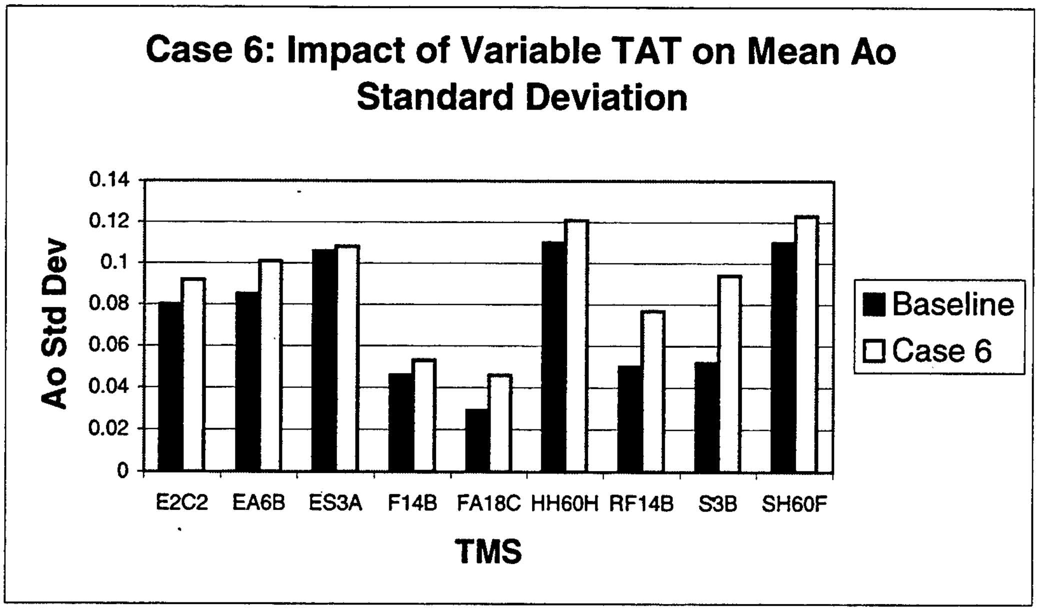

Figure 25. Case 6, Impact of Variable TAT on Mean Ao Standard Deviation

The minimum observed values of Ao are decreased for all TMSs in Case 6. This decrease is caused partially by increased variability and partially by the higher expected values of actual TAT data described above. Change to the maximum observed values of Ao is mixed. Five TMSs experience an increase in maximum observed Ao and four experience a decrease.

The overall impact of variable TAT on Ao is similar to that described in Case 4c. The increased variability of the system has resulted in a flattening and stretching of the PDF of Ao. Figure 26 and Figure 27 graphically illustrate the impact of increased variability on Ao.

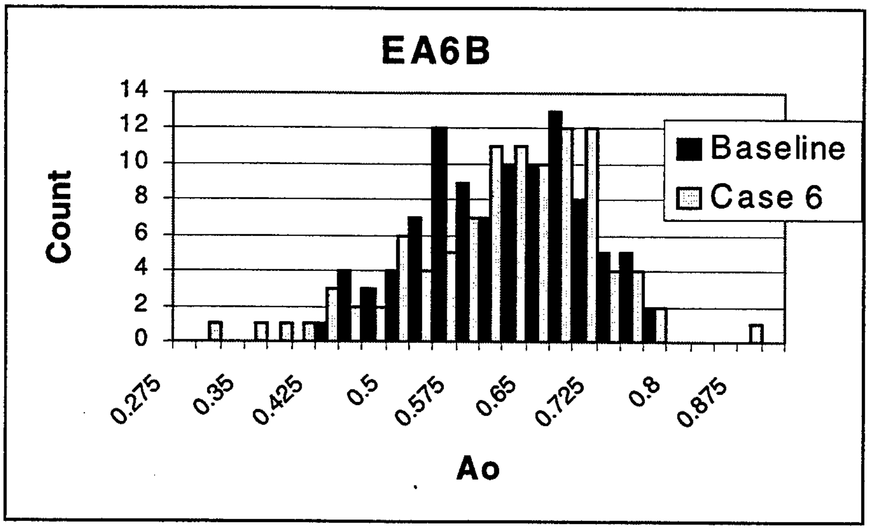

Figure 26. Case 6, EA6B, Impact of Increased Variability on the Distribution of Ao

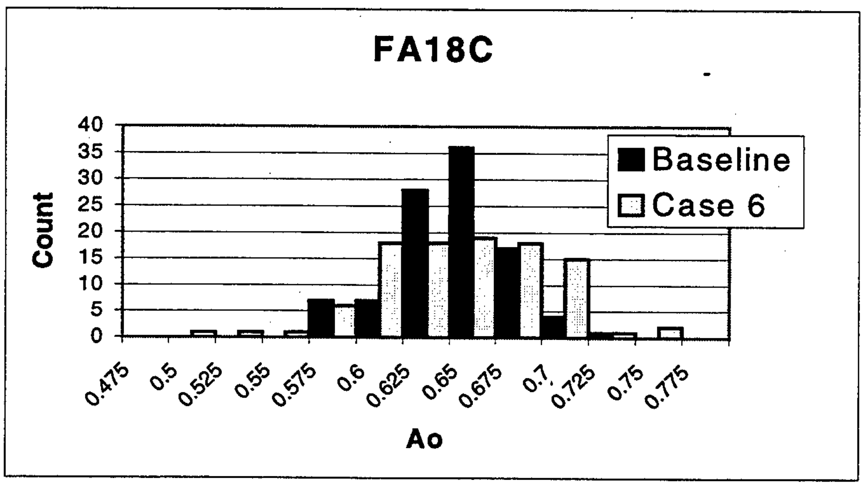

Figure 27. Case 6, FA18C, Impact of Increased Variability on the Distribution of Ao

The EA6B and FA18C clearly demonstrate the flattening of the Ao PDF due to increased variability. These TMSs are selected because of the small change in their mean Ao, isolating the impact of variability.

7. Case 7, Analysis of Cannibalization

Cannibalization is the removal of an RFI item from an aircraft that is already down for use in repairing another aircraft. Cannibalization occurs when the supply-maintenance system fails to provide RFI material in a timely enough fashion to meet the requirements of aircraft operators and maintainers. Operators and maintainers use cannibalization to increase Ao by consolidating material deficiencies to a small number of aircraft.

Cannibalization is not considered in the ARROWs allowance model. An unstated goal of ARROWs is to prevent or minimize the need for cannibalization by providing adequate allowances of spare WRAs. Despite this fact, cannibalization plays a significant part in maintaining the level of Ao required by fleet operators and maintainers. Given that cannibalization takes place, it is desired to characterize and quantify its impact on Ao. This is accomplished by incorporating cannibalization into the simulation and comparing the resulting TMS Ao's with those of the baseline.

The level of cannibalization intended to be added into the simulation is light to moderate as opposed to heavy. Heavy cannibalization is characterized by down aircraft that are never returned to an "up" status. Instead, these aircraft act solely as a source of RFI WRAs for other aircraft. Light cannibalization is characterized by situational use only. The intent of light cannibalization is to improve overall TMS Ao without relegating individual aircraft to a perpetual down state. To control the level of cannibalization included in the simulation, the following guidelines are established.

- An aircraft is only eligible to receive a cannibalized WRA if the number of WRAs required to return that aircraft to an up status is equal to one.

- Cannibalization is limited to aircraft among a single TMS. For example, a WRA cannot be cannibalized from an F14B to return an FA18C to an up status.
- The number of cannibalized WRAs that can be taken from any aircraft is limited to three per downtime.

Simulated cannibalization is a function of the air-wing object. At the conclusion of each flying day, the air-wing object examines each aircraft in the down aircraft vector to determine if cannibalization can be applied using the guidelines listed above. If a cannibalization occurs, the appropriate WRA and its embedded Time To Failure (TTF) are moved from the giving aircraft to the receiving aircraft. The air-wing then records the cannibalization by incrementing a TMS specific counter. Total cannibalizations, by TMS, are available in the simulation output report, Appendix J. Figure 28 compares the mean Ao for this excursion with the baseline.

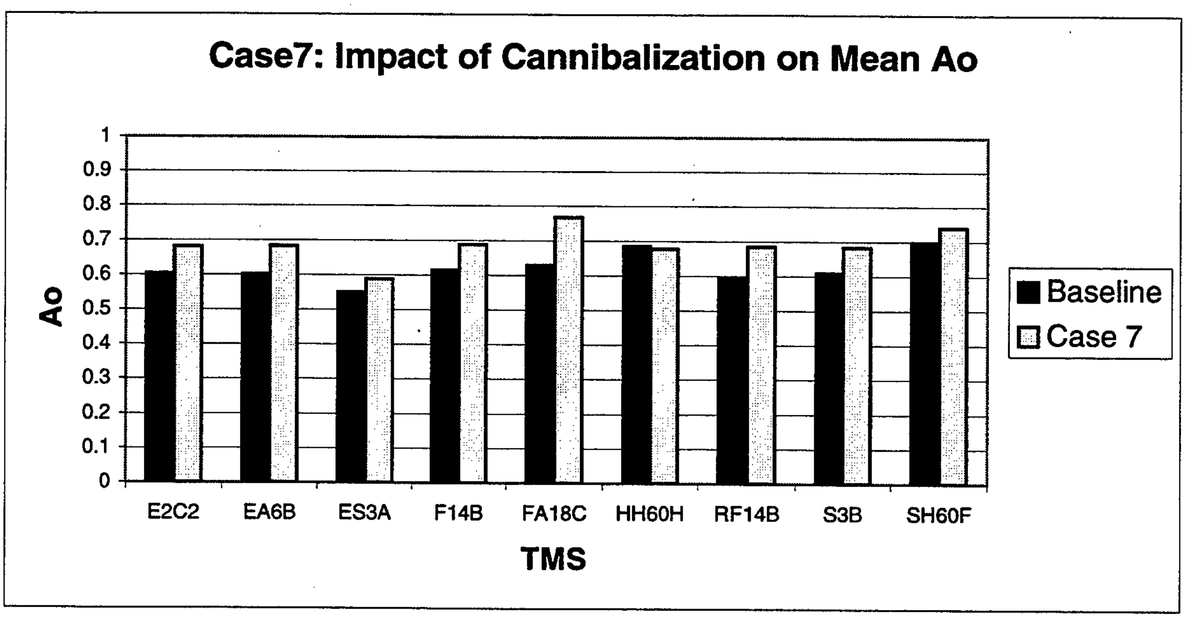

Figure 28. Case 7, Impact of Cannibalization on Mean Ao

The introduction of cannibalization positively impacts Ao. Cannibalization raises the mean Ao and reduces the standard deviation for eight of the nine TMSs. The average increase in mean Ao across all TMS is 0.07. The only TMS that did not see measurable improvement as a result of cannibalization is the HH60H. HH60H mean Ao and standard deviation remains largely unchanged from the baseline.

Appendix J includes specific details on the level of cannibalization taking place in the simulation. This data is summarized in Table 8. Also included in Table 8 is cannibalization data from five carrier air-wing deployments. Both simulated and actual cannibalization data has been normalized on a "per aircraft per 90 day" basis to allow for easier direct comparison.

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Simulated	3.5	4.3	3.5	6.8	6.3	1.5	2.5	6.0	1.6
Hist. Data	23.7	18.8	10.0	12.0	9.8	1.9	No Data	27.7	2.5

Table 8. Cannibalizations per Aircraft per 90 Days, Simulated Values and Historical Record of Five Carrier Air-Wings

The simulated level of cannibalization is considerably more modest than that observed in actual air-wings. The simulation has also failed to capture the fact that the cannibalization rate is highest among TMSs with small populations. Even with this highly conservative estimate, cannibalization has considerable positive impact on Ao.

Examination of Supply Department and AIMD performance measures (see Appendix J), as expected, reveals no significant departures from the baseline due to the incorporation of cannibalization.

8. Case 8, Analysis of AVCAL Allowances

The WRA allowances determined by ARROWs are subject to review prior to publication in the Aviation Coordinated Allowance List (AVCAL). Reviews are generally referred to as provisioning conferences. Provisioning conferences are held so representatives from the fleet along with technical and maintenance personnel can review the ARROWs WRA allowances and recommend necessary changes.

Reasons for altering the ARROWs WRA allowances are many and diverse. They include, past allowance levels, demand data, recent failure rates, current technical issues, configuration changes and safety stock levels for mission critical, low failure rate material. Figure 29 provides a summary of the changes made to the ARROWs WRA allowances prior to their publication in the AVCAL for the USS GEORGE WASHINGTON air-wing.

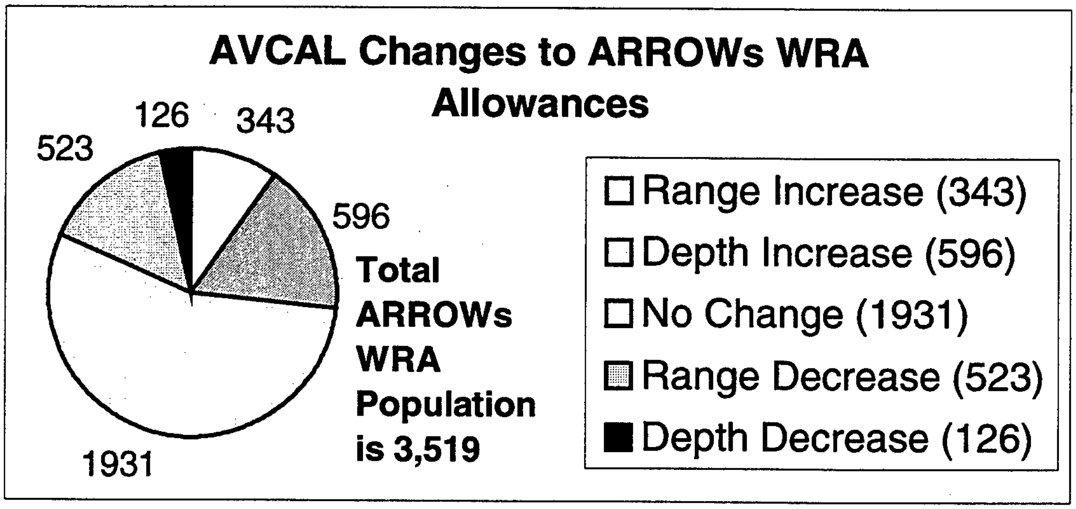

Figure 29. AVCAL Changes To ARROWs WRA Allowances

Changes in range apply to whether or not an item is stocked at all. A range increase indicates that ARROWs established an allowance of zero for a particular WRA,

and that allowance was increased in the AVCAL to some number greater than zero. A range decrease implies ARROWs established an allowance greater than zero, and that allowance was changed to zero in the AVCAL.

Changes in depth apply to WRAs whose allowance is greater than zero for both ARROWs and the AVCAL. A depth increase indicates that the AVCAL WRA allowance is greater than the ARROWs allowance. A depth decrease indicates that the AVCAL allowance is less than the allowance determined by ARROWs.

The intent of changes to the ARROWs WRA allowances is to increase supply effectiveness and improve Ao. This is done primarily through the supplementing of ARROWs allowances through range and depth increases based on more accurate information than is available in the ARROWs candidate file.

The majority of range and depth decreases are the result of changes to aircraft configurations. Typically, a new WRA, not included in the ARROWs candidate file or allowances, is added to the AVCAL in lieu of the WRA removed. The net effect is that WRA allowances are not actually decreased; just changed to reflect configuration changes. Visibility of these type changes is not possible with the data available.

Case 8 examines the impact of supplements to the ARROWs allowances only. Decreases in WRA allowance range and depth are assumed to be the result of configuration churn not actual reductions in allowance levels. To lend a sense of proportion, the ARROWs WRA allowances are characterized by a total range of 2,013 and a total depth of 3,236. The supplemented AVCAL WRA allowances are characterized by a total range of 2,356 and a total depth of 4,466. The results of Case 8

are summarized in Appendix K. Figure 30 compares the mean Ao achieved by the AVCAL WRA allowances and that of the baseline. [Ref. 18]

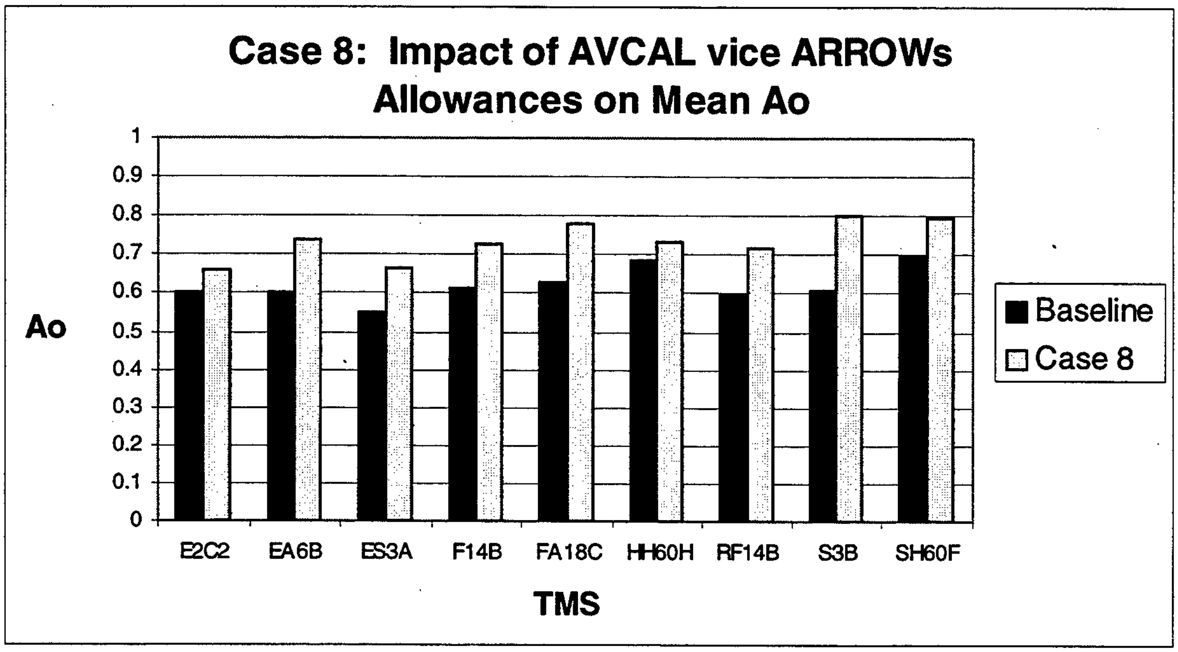

Figure 30. Case 8, Impact of AVCAL vice ARROWs Allowances on Mean Ao

The impact of supplementing WRA allowance quantities is, not surprisingly, uniformly positive. Mean Ao and minimum observed Ao increase an average of 0.11 for all TMSs. Maximum observed Ao increases an average of 0.08 for all TMSs. Mean Ao standard deviation is reduced for eight of the nine TMSs. The HH60H experienced a small increase in standard deviation.

The reason for the improvement in Ao is a dramatic reduction in NC and NIS demands (see Appendix K). The quantity of NC demands is reduced 69% from the baseline simulation. The number of NIS demands is decreased by 29%. These reductions explain all other system departures from the baseline simulation.

9. Case 9, Analysis of Simulation with full Functionality

This excursion combines all of the functionality described in Cases 1 through 8 into a single simulation excursion. Case 9 is characterized by;

- The 180 day actual flight schedule flown by the USS GEORGE WASHINGTON's air-wing
- Prioritized, variable OST based on the OST analysis conducted by the Center for Naval Analysis (CNA)
- Variable TAT based on one year of afloat maintenance actions
- Modest cannibalization
- Actual AVCAL allowances

Prioritized repair is not incorporated into Case 9 due to its unintended impact on Supply effectiveness as described in paragraph IV.C.5. The results of Case 9 are summarized in Appendix L.

a. Comparison of the Full Simulation to the Baseline Simulation

The baseline simulation is constructed using the ARROWs assumptions and provides estimates of mean Ao that are very close to those calculated by ARROWs. The full simulation includes a variety of functionality not included in ARROWs due to simplifying assumptions. The differences between the baseline simulation and the full simulation can be characterized as the "cost", in terms of Ao, of the ARROWs assumptions. Figure 31 compares the baseline/ARROWs mean Ao with that achieved by the full simulation.

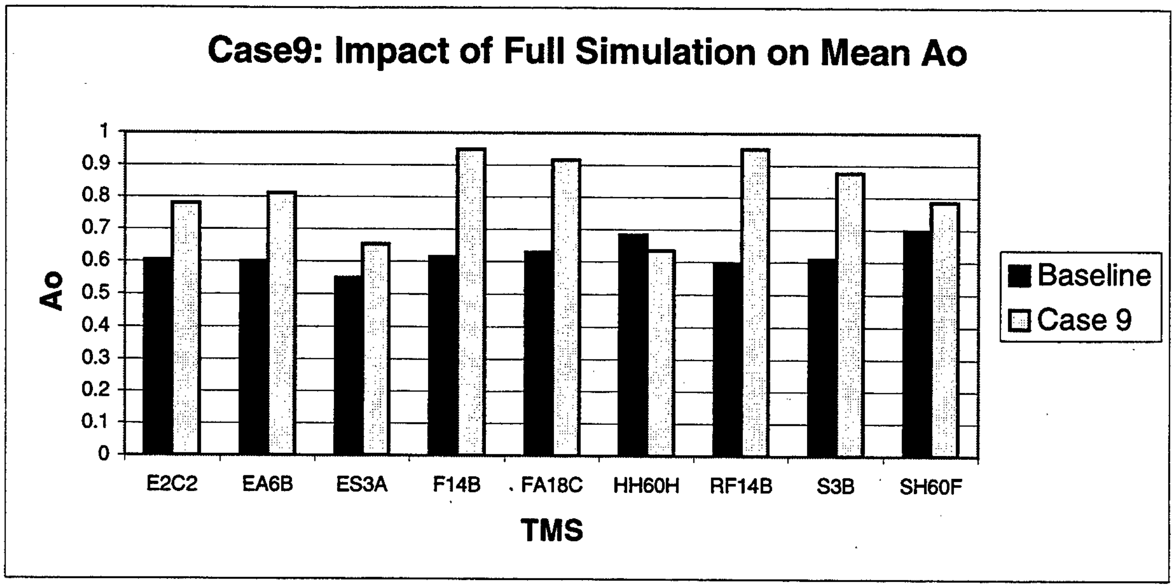

Figure 31. Case 9, Impact of Full Simulation on Mean Ao

Simultaneous inclusion of all simulation functionality dramatically improves mean Ao for all TMSs with the exception of the HH60H. Average improvement in Ao across all TMSs is 0.20. The standard deviation of mean Ao is reduced for seven of nine TMSs. The overall result is a shift in the Ao PDF towards higher Ao and tightening of the PDF around mean Ao. This effect is presented graphically in Figure 32 for the FA18C.

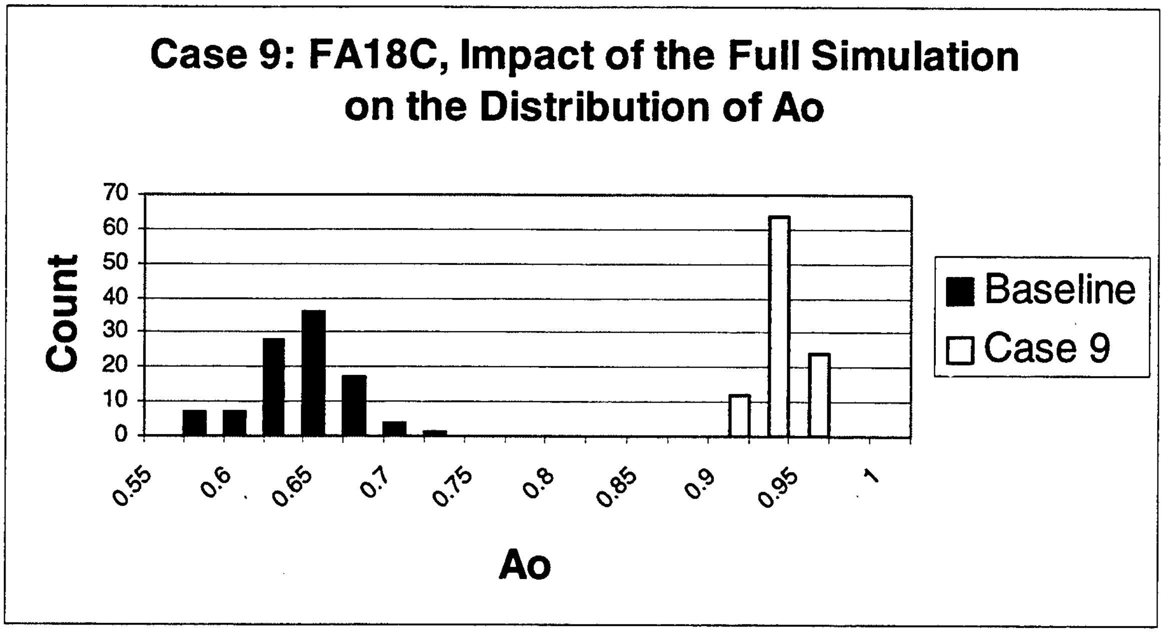

Figure 32. Case 9, FA18C, Impact of the Full Simulation on the Distribution of Ao

The reasons for this dramatic increase in Ao are reduced flight hours and supplemented WRA allowances. In the full simulation, gross supply effectiveness is 95.2% compared to 87.6% in the baseline simulation. This increase equates to a 63% reduction in the number of WRA failures not satisfied with a Supply Department issue. This reduction combined with a very modest level of cannibalization results in the overwhelming majority of aircraft downing WRA failures being satisfied within hours. In the baseline simulation, 12.4% of total demands were satisfied with an EXREP, DTO requisition, or stock diversion.

b. Comparison of the Full Simulation to Actual Fleet FMC

The results of the baseline and full simulation are now compared to the actual Ao achieved by the USS GEORGE WASHINGTON air-wing during the deployment modeled. This comparison is used to determine if either simulation is a good predictor of the Ao actually achieved by the air-wing modeled.

Fleet Ao data is of two types, Full Mission Capable (FMC) and Mission Capable (MC) as described in Chapter II. ARROWs and the simulation model FMC so comparisons will not address MC. The fleet FMC data used in this analysis is obtained from the Subsystem Capability and Impact Reporting (SCIR) database. SCIR FMC observations are provided on a per squadron per month basis. Note that RF14Bs are excluded from this analysis because no SCIR data is available for this TMS.

Figure 33 provides the mean values of Ao for the baseline simulation (representative of ARROWs), the full simulation (Case 9), and the SCIR FMC data for the USS GEORGE WASHINGTON's air-wing.

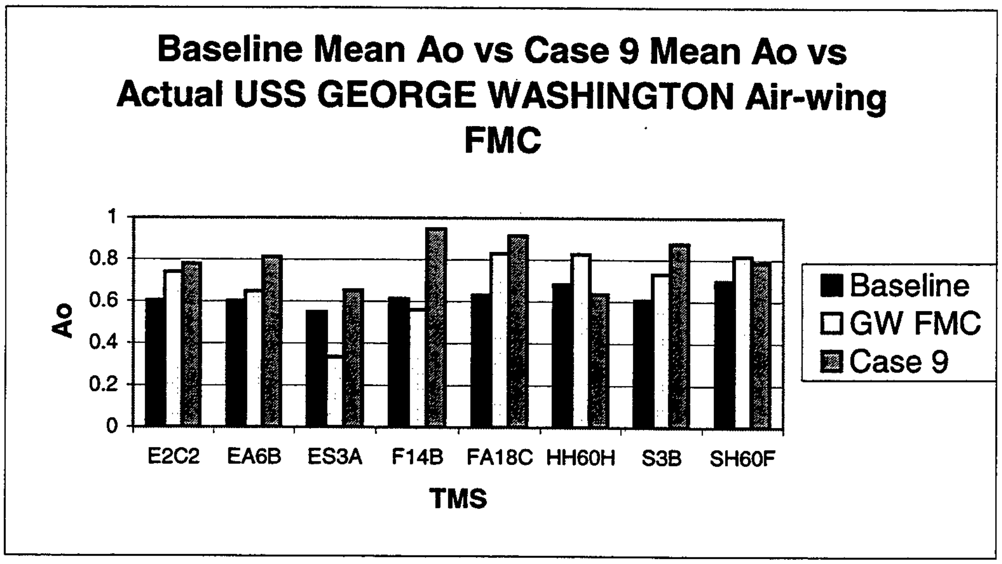

Figure 33. Case 9, Baseline Mean Ao vs Case 9 Mean Ao vs Actual USS GEORGE WASHINGTON Air-Wing FMC

Neither the baseline nor the full simulation serve as a particularly accurate predictor of actual air-wing FMC. Discrepancies in mean Ao between simulated and actual data vary by TMS. In general, the baseline (and ARROWs) tends to underestimate actual FMC and the full simulation tends to overestimate actual FMC. ARROWs and the

baseline simulation underestimate actual FMC in six of eight TMSs. Likewise, the full simulation overestimates actual FMC in six of eight TMSs.

In addition to forecasting mean Ao, the full simulation attempts to model the variability of Ao by including variable OST and TAT into the model. To examine how well variability has been captured, the FA18C is examined in greater detail. The FA18C is presented for three reasons.

- FA18Cs constitute a large percentage of the air-wing and are therefore of high interest.
- There are three FA18C squadrons in the air-wing. All other TMSs have only one squadron. SCIR FMC is reported on a per squadron per month basis. As such, there are 18 observations of FA18C actual FMC for the six month deployment. All other TMSs have just six observations.
- The FA18C is characteristic of most TMSs in that the baseline simulation underestimates true mean FMC and the full simulation overestimates true FMC.

Figure 34 provides a side by side comparison of the Ao histograms for the FA18C resulting from the baseline simulation, the full simulation and the SCIR FMC data. The histograms are presented in this fashion to allow easy comparison of the mean/median Ao and the relative variability present in the observations. Direct comparison of actual Ao counts per bin is not possible due to the differences in total observations presented.

The SCIR FMC data represents 18 observations. Each simulation represents 100 observations. In order to present the data in the most meaningful way, the

"y" or "count" axis has been truncated at 10. This prevents the 18 SCIR FMC observations from being "drowned out" by the more numerous simulated observations. The actual heights of the baseline and full simulation histograms are the same as presented in Figure 32.

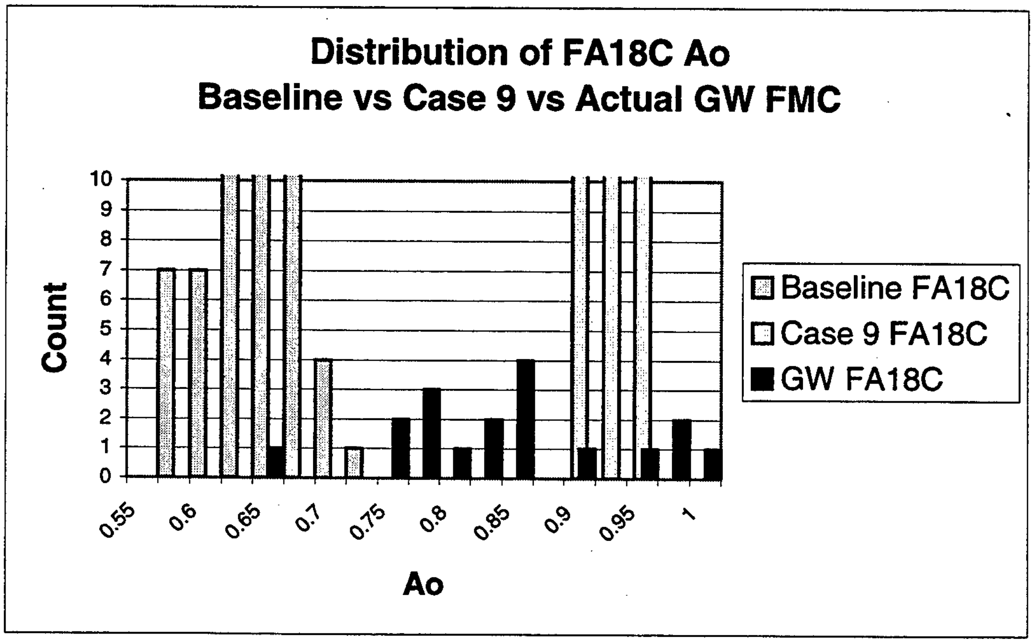

Figure 34. Case 9, Distribution of FA18C Ao, Simulated vs Actual FMC

Figure 34 indicates that the true variability of FA18C Ao is not well captured by either simulation. Efforts to capture the overall variability of Ao through the incorporation of variable OST and TAT are masked by other factors. Cannibalizations, reduced flying hours and supplemented allowances all reduce the variability of Ao.

The full simulation is unsuccessful it its attempt to provide a highly accurate estimation of the mean and variance of actual Ao. The full simualtion is relatively complex when compared to ARROWs or the baseline simulation. However, the system being modeled, an operational air-wing and its supporting supply-maintenance infrastructure, is infinitely more complex.

The full simulation yields distributions of Ao that are characterized by an overestimation of mean Ao and an underestimation of the variability of mean Ao. Three subjective explanations are offered to explain this discrepancy.

- **Significant factors that impact FMC are Excluded from the Simulation:** The number of factors that could be listed here are infinite. Crew skill and training levels, ship's schedule and test bench availability all impact FMC but are not incorporated in the simulation. Inefficiencies in the movement of failed and RFI WRAs between squadron level maintainers, supply and the AIMD could also significantly impact actual fleet FMC but are assumed to be zero in the simulation.
- **WRA Failures Rates**: The simulation creates WRA allowances based on the assumption that the time between WRA failures is exponentially distributed with a mean value based on point estimates for Maintenance Replacement Factor (MRF) and Rotable Pool Factor (RPF). Variations from this WRA demand rate are likely. Variations could be the result of some WRA failures not being exponentially distributed, errors in the point estimates of MRF and RPF or WRA wear out due to repeated repair. The impact of higher than anticipated demand is reflected in the distribution of actual fleet FMC. The simulation however, is immune to unanticipated demands.
- **Impact of Zero Failure WRAs**: The ARROWs candidate file, on which the simulation is based, identifies 3,519 unique WRAs in the air-wing deckload. Of these, 1,576 have a zero failure rate. This means that 45% of all WRAs are precluded from failure in the full simulation. In actuality, nothing has a zero

failure rate. It is worthy of note that the AVCAL provides allowances for 361 of these zero failure rate WRAs. These allowances are commonly referred to as "insurance items". The impact of failures to all these items is reflected in actual fleet FMC levels but is omitted from the full simulation.

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V. CONCLUSIONS AND RECOMMENDATIONS

The goals of this thesis are to characterize the distribution of Operational Availability (Ao) and to quantify the impact on Ao of various factors not included in the ARROWs model. These goals are successfully achieved.

A. CHARACTERIZING THE DISTRIBUTION OF Ao WITH THE BASELINE SIMULATION

1. Summary of Findings for the Baseline Simulation

The baseline simulation developed for this thesis has closely approximated the point estimate for mean Ao provided by ARROWs for a specific allowance list of WRAs. Further, it has demonstrated that Ao is a random variable and improves on the ARROWs point estimate by quantifying the variability and characterizing the Probability Density Function for mean Ao.

The standard deviation of mean Ao is based on the simulated mean Ao values. The calculated values of the standard deviation for mean Ao are well approximated by the following non-linear model:

$$\hat{s}_{ARROWs\_TMS\_\bar{A}o} \approx (0.16) \cdot (TMS\_population)^{-0.5}$$

Equation 1.

The simulated values of mean Ao are shown to be distributed Lognormal(μ , σ). The parameters μ and σ for this distribution are determined using the mean value for Ao and the standard deviation of mean Ao obtained from the simulation and the following formulas:

$$\mu \approx \ln(Simulated\_TMS\_\overline{A}o) - \frac{\sigma^2}{2}$$

Equation 2.

$$\sigma \approx \sqrt{\ln\left(\frac{\hat{s}^2_{Simulated\_TMS\_\overline{A}o}}{(Simulated\_TMS\_\overline{A}o)^2} + 1\right)}$$

Equation 3.

2. Conclusions Regarding the Baseline Simulation

The baseline simulation incorporates the assumptions on which the ARROWs allowance model is based and closely approximates the mean value of Ao calculated by ARROWs. By the Central Limit Theorem, the theoretical distribution of the ARROWs mean Ao is approximately Lognormal(μ, σ). The baseline simulation generates simulated values of mean Ao that are consistent with a Lognormal(μ, σ) distribution. Based on these findings, the distribution of ARROWs mean Ao is characterized as Lognormal(μ, σ).

The distribution of ARROWs mean Ao can be approximated without the use of the simulation and is accomplished as follows.

- Substitute the ARROWs calculated mean value of Ao for the simulated mean Ao.
- Estimate the ARROWs standard deviation of mean Ao using the non-linear model, Equation 1. Substitute this value for the simulated standard deviation of mean Ao.

- Determine the estimates for the parameters μ and σ for the Lognormal distribution using the ARROWs calculated mean value of Ao, the estimated ARROWs standard deviation of mean Ao, and Equations 2 and 3.

The resulting PDF serves as an approximation of the baseline simulation developed by this thesis. Figure 35 presents the approximated PDF for FA18C mean Ao and the PDF developed by the simulation. The vertical dotted line is the target value of Ao used as an input to the ARROWs model.

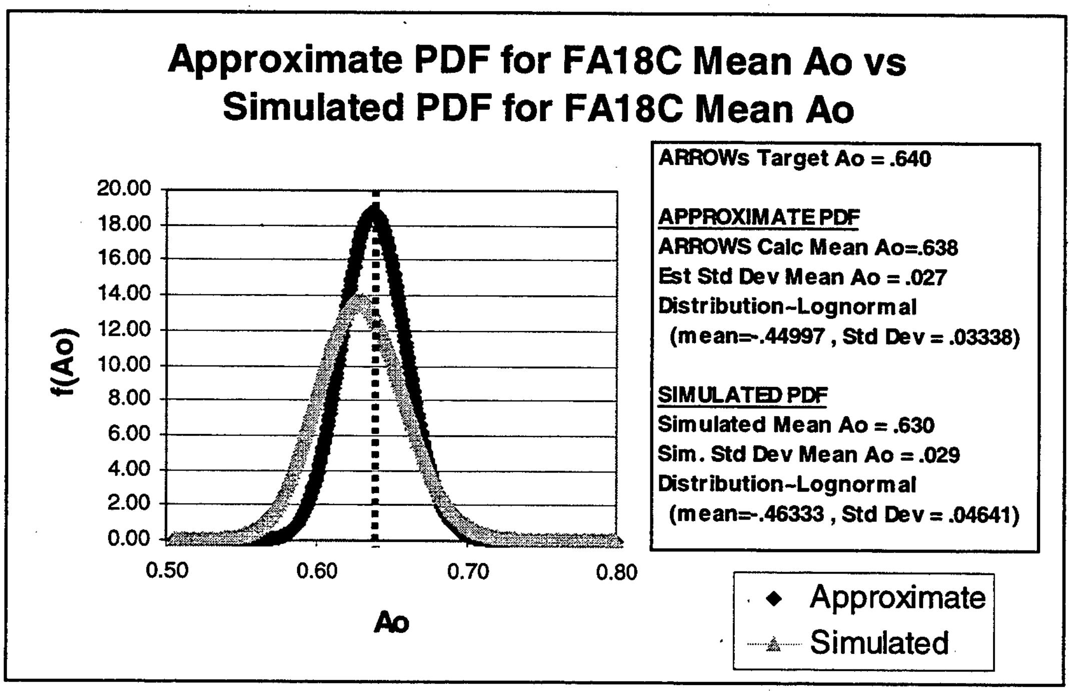

Figure 35. Approximate PDF for FA18C Mean Ao vs Simulated PDF for FA18C Mean Ao

Figure 35 demonstrates that the approximate PDF closely resembles the PDF developed as a result of the simulation. The simulated mean Ao for the FA18C is 0.008 less than the mean Ao calculated by ARROWs resulting in a corresponding shift in the PDF. The estimate of standard deviation used in the approximate PDF is slightly less

than that observed in the simulation resulting in a corresponding tightening of the approximate PDF about its mean value.

These conclusions provide the ARROWs user with considerably more information about the calculated ARROWs mean Ao than a point estimate.

B. QUANTIFYING THE IMPACT ON Ao OF VARIOUS FACTORS NOT INCLUDED IN THE ARROWS MODEL WITH SIMULATION EXCURSIONS

1. Summary of Findings for the Simulation Excursions

ARROWs uses closed form equations to estimate the mean or expected value of Ao based on a specific mix of spare WRAs. This estimate is based on a variety of simplifying assumptions that treat all random variables as constants with the exception of WRA failure times. Due to mathematical complexity, ARROWs is unable to deviate from these assumptions. The simulation developed for this thesis is not similarly constrained. The baseline simulation has been expanded to include a variety of more complex factors. Comparison of the results of these scenarios against the baseline allows the resulting impact on Ao to be quantified.

Table 9 summarizes the various excursions in terms of their impact on mean Ao and the standard deviation of mean Ao. The data in this table represents change in air-wing Ao. Impact of the various scenarios on individual Type Model Series (TMS) has been normalized to summarize the impact on the air-wing as a whole.

Baseline: Air-wing Mean Ao = .621 Air-wing S.D. Mean Ao = .049	**Mean Ao Change From Baseline**	**Mean Ao % Change From Baseline**	**S.D. Mean Ao Change From Baseline**	**S.D Mean Ao % Change From Baseline**
Case1: 180 vice 90 Day Support Period	-0.014	-2.2%	-0.011	-22.5%
Case2: Actual Flight Schedule (90 Days)	0.224	36.1%	-0.018	-37.1%
Case3: Prioritized Requisitioning (Static) (hi-pri 9 Days, routine 27Days)	0.001	0.2%	-0.006	-11.8%
Case4a: Variable Order and Shipping Time (hi-pri exp(20), routine exp(20))	0.013	2.0%	0.003	6.3%
Case4b: Variable Order and Shipping Time (hi-pri exp(9), routine exp(27))	0.016	2.6%	-0.005	-9.5%
Case4c: Variable Order and Shipping Time (hi-pri exp(22), routine exp(36)	-0.071	-11.5%	0.017	35.4%
Case5: Prioritized Repair	0.099	15.9%	-0.005	-9.7%
Case6: Variable Turn Around Time (TAT)	-0.031	-5.1%	0.018	37.2%
Case7: Cannibalization	0.100	16.2%	-0.014	-28.5%
Case8: AVCAL vice ARROWs WRA Allowances	0.134	21.6%	-0.009	-17.6%
Case9: Full Simulation	0.268	43.2%	-0.019	-38.3%

Table 9. Impact of the Various Simulation Excursions On Mean Ao and the Standard Deviation of Mean Ao

2. Conclusions Regarding The Simulation Excursions

The simulation has shown that varying the assumptions and parameters upon which the model is based has the effect of altering the PDF of Ao. Impacts to mean Ao shift the PDF along the Ao axis. Impacts to the standard deviation of mean Ao stretch or contract the PDF of mean Ao about its mean value. The magnitude of changes to the PDF of mean Ao varies with the particular excursion being examined. The following conclusions apply without exception:

- Mean Ao is positively impacted by reductions in flying hours, increases in WRA allowances and cannibalization.
- The variability associated with Order and Shipping Times (OSTs) and repair Turn Around Times (TATs) increases the variability of Ao.
- Mean Ao is more sensitive to changes in TAT than in OST. This is a result of the fact that the majority of Ready For Issue (RFI) WRAs, for use in the repair of aircraft or to re-supply the Supply Department, are furnished by the AIMD not by off-ship requisitions.
- Changes in OST impact Ao but the impact is mixed.
- Decreasing the OST for hi-priority, DTO requirements positively impacts Ao. These benefits are offset by increases in routine priority OST for stock replenishment requisitions which negatively impact Ao.
- The negative impact of increased OST for stock replenishment requisitions is felt in two ways. First, because stock is not replaced in a timely fashion, the number of Not In Stock (NIS) demands increases. Second, the increased NIS rate impacts the mix of WRAs requiring Expedited Repair (EXREP) resulting in a higher EXREP Beyond the Capability of Maintenance (BCM) rate.

The conclusions described above are intuitively compelling and are consistent with the actual performance of the supply-maintenance system onboard an aircraft carrier.

C. GENERAL CONCLUSIONS

1. The Full Simulation

The baseline simulation is constructed on the assumptions of the allowance model ARROWs. Additional functionality was incrementally added to more accurately reflect the operations of a carrier air-wing and the supply-maintenance system that supports it. The full simulation, with all functionality included, is intended to provide an accurate tool for forecasting the FMC levels of operational aircraft squadrons.

Analyses of the results of this simulation indicate that neither the full simulation nor ARROWs (baseline simulation) accurately forecasts FMC. The full simulation overestimates fleet FMC, and ARROWs underestimates FMC. Both the baseline and the full simulation underestimate the variability associated with actual FMC rates. It appears that this relatively complex simulation has not adequately captured the highly complex system of aircraft, their WRAs, WRA failures and replacements, repair and requisitioning, and people. The simulated results are of the correct order of magnitude but lack the precision required for accurate forecasting.

2. ARROWs Assumptions

The simulation developed for this thesis makes every effort to include actual data vice assumptions whenever possible. To this end, all ARROWs assumptions are closely investigated and compared to actual data if possible. The following ARROWs assumptions are inconsistent with actual data.

- ARROWs assumes a 90 day support period when actual carrier air-wing deployments are approximately 180 days in duration.

- ARROWs assumes a flight hour program significantly greater than those being executed by actual carrier air-wings.
- ARROWs develops WRA allowances based on a Readiness Based Sparing (RBS) algorithm. These allowances are significantly supplemented prior to publication in the AVCAL indicating 1) a lack of faith in the ARROWs RBS allowances and or 2) a lack of discipline in the allowance development process that allows operators to significantly increase WRA allowances.
- ARROWs assumes that WRA failure times are exponentially distributed with a Mean Time Between Failure indicated by point estimates for Maintenance Replacement Factor (MRF) and Rotable Pool Factor (RPF). Inaccuracy in either the distribution selection or parameter estimation has serious implications for both allowance computation and Ao. Increased emphasis on individual WRA reliability appears warranted.

D. RECOMMENDATIONS FOR FURTHER RESEARCH

This thesis has demonstrated that Ao is a random variable with a distribution, mean and variance. This characterization of Ao provides significantly more information about Ao than is available from ARROWs. However, the need for a robust Ao forecasting tool for fleet aircraft squadrons has not been satisfied by this thesis. Such a tool is still considered highly desirable. The simulation in this thesis, like ARROWs, attempts simply to model FMC. A more useful tool would distinguish between WRA failures that result in Partially Mission Capable (PMC) failures and Non Mission Capable (NMC) failures so that Mission Capable (MC), in addition to FMC rates, could be forecast.

The allowance model ARROWs and the simulation developed for this thesis rely on the assumption that WRA failures occur like events in a Homogeneous Poisson Process. This assumption appears to be driven by the stochastic calculations performed by ARROWs and a lack of reliability data for WRAs.

It is intuitively appealing that allowances for spare parts, as important and as expensive as aircraft WRAs, be developed on reliability data, not on assumptions made for mathematical convenience. This thesis has attempted to demonstrate that simulation is capable of incorporating a wide variety of very complex functionality precluded by stochastic models such as ARROWs. The incorporation of actual reliability data into the allowance development process is the natural successor to the first generation RBS models such as ARROWs. Use of simulation and WRA reliability data for actual allowance development should be further examined.

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Appendix A. Baseline Simulation Results

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Static 20 Days		
Priority Repair:	No	Routine OST:	Static 20 Days		
Cannibalization:	No	WRA Allowances:	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.604	0.601	0.550	0.614	0.630	0.684	0.596	0.608	0.698
Std Dev	0.080	0.085	0.106	0.046	0.029	0.110	0.050	0.052	0.110
Median	0.611	0.608	0.554	0.615	0.633	0.689	0.604	0.610	0.701
Min	0.418	0.402	0.290	0.473	0.550	0.440	0.473	0.457	0.396
Max	0.768	0.763	0.767	0.708	0.700	0.893	0.699	0.714	0.918

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7257.5	5550.4	1443.6	271.0	1027.0	911.1	70.9	44.3
Std Dev	80.5	66.5	40.1	3.4	52.3	48.3	11.4	2.3
Median	7256.5	5546.5	1447.5	271.0	1024.0	908.5	71.0	44.3
Min	7073.0	5331.0	1339.0	261.2	918.0	803.0	50.0	39.1
Max	7508.0	5746.0	1538.0	280.5	1147.0	1031.0	107.0	49.7

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8284.6	7257.5	123.8	903.2	70.9	1443.6	0.889	0.876	613.9
Std Dev	100.1	80.5	12.1	50.5	11.4	40.1	0.005	0.006	28.2
Median	8291.0	7256.5	122.5	898.5	71.0	1447.5	0.890	0.877	617.5
Min	8053.0	7073.0	95.0	799.0	50.0	1339.0	0.876	0.862	546.0
Max	8567.0	7508.0	153.0	1026.0	107.0	1538.0	0.900	0.888	671.0

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Appendix B. Case 1: 180 vice 90 Day Support Period

Simulation Settings

Support Period	180 Days	**Variable TAT:**	No	**Runs:**	100
Flight Schedule:	Wartime	**Hi-Priority OST:**	Static 20 Days		
Priority Repair:	No	**Routine OST:**	Static 20 Days		
Cannibalization:	No	**WRA Allowances:**	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.584	0.570	0.530	0.608	0.617	0.661	0.594	0.587	0.674
Std Dev	0.065	0.059	0.067	0.027	0.025	0.084	0.040	0.047	0.084
Median	0.586	0.574	0.526	0.605	0.621	0.666	0.594	0.592	0.682
Min	0.403	0.405	0.337	0.539	0.558	0.367	0.503	0.479	0.401
Max	0.709	0.707	0.681	0.684	0.676	0.838	0.680	0.700	0.862

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	14475.4	11349.6	2864.2	274.2	2088.7	1894.5	150.4	45.7
Std Dev	101.3	86.7	53.1	2.4	80.2	74.8	17.6	1.9
Median	14481.0	11351.0	2861.5	274.3	2084.5	1888.5	149.0	45.7
Min	14216.0	11097.0	2747.0	268.2	1932.0	1740.0	116.0	41.8
Max	14725.0	11567.0	3016.0	280.3	2310.0	2098.0	221.0	50.3

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	16564.2	14475.4	248.3	1840.5	150.4	2864.2	0.887	0.874	1264.0
Std Dev	128.7	101.3	16.6	78.9	17.6	53.1	0.004	0.004	48.1
Median	16582.5	14481.0	248.5	1836.5	149.0	2861.5	0.887	0.874	1264.5
Min	16148.0	14216.0	220.0	1666.0	116.0	2747.0	0.875	0.862	1165.0
Max	16816.0	14725.0	287.0	2051.0	221.0	3016.0	0.897	0.882	1376.0

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Appendix C. Case2: Actual Vice Notional Flight Schedule

Simulation Settings

Support Period	90 Days	**Variable TAT:**	No	**Runs:**	100
Flight Schedule:	Actual	**Hi-Priority OST:**	Static 20 Days		
Priority Repair:	No	**Routine OST:**	Static 20 Days		
Cannibalization:	No	**WRA Allowances:**	ARROWs		

Ao Statistics

	E2C2	**EA6B**	**ES3A**	**F14B**	**FA18C**	**HH60H**	**RF14B**	**S3B**	**SH60F**
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.783	0.738	0.644	0.937	0.840	0.683	0.947	0.826	0.795
Std Dev	0.060	0.064	0.089	0.016	0.018	0.099	0.016	0.039	0.087
Median	0.788	0.743	0.640	0.939	0.843	0.691	0.949	0.828	0.797
Min	0.650	0.567	0.411	0.894	0.795	0.326	0.878	0.679	0.595
Max	0.925	0.869	0.815	0.971	0.886	0.885	0.973	0.912	0.956

AIMD Statistics

	Stock Inductions	**Stock Repairs**	**Stock BCMs**	**Time Avg # of Stock In Repair**	**EXREP Inductions**	**EXREP Repairs**	**EXREP BCMs**	**Time Avg # of EXREPs In Repair**
Mean	4088.0	3056.7	872.4	151.9	280.9	244.3	25.3	12.4
Std Dev	64.9	54.8	33.2	2.9	19.7	20.0	5.6	1.0
Median	4094.5	3060.5	868.0	151.9	281.0	242.5	26.0	12.3
Min	3890.0	2921.0	806.0	144.2	238.0	207.0	11.0	10.4
Max	4231.0	3215.0	958.0	159.5	326.0	294.0	46.0	15.3

Supply Dept. Statistics

	Demands	**Issues**	**Not Carried**	**Not In Stock**	**DTO Reqns**	**Stock Reqns**	**Net Eff**	**Gross Eff**	**Stock Diversions**
Mean	4368.8	4088.0	72.0	208.8	25.3	872.4	0.951	0.936	167.5
Std Dev	71.9	64.9	9.4	17.6	5.6	33.2	0.004	0.004	14.4
Median	4370.0	4094.5	71.0	208.0	26.0	868.0	0.952	0.935	165.0
Min	4128.0	3890.0	49.0	170.0	11.0	806.0	0.943	0.926	128.0
Max	4528.0	4231.0	98.0	251.0	46.0	958.0	0.959	0.946	203.0

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Appendix D. Case3: Prioritized Order and Shipping Time

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Static 9 Days		
Priority Repair:	No	Routine OST:	Static 27 Days		
Cannibalization:	No	WRA Allowances:	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.617	0.615	0.549	0.603	0.637	0.685	0.588	0.594	0.717
Std Dev	0.067	0.079	0.090	0.041	0.024	0.090	0.050	0.053	0.086
Median	0.619	0.623	0.545	0.602	0.638	0.693	0.584	0.594	0.721
Min	0.456	0.339	0.319	0.517	0.563	0.473	0.467	0.417	0.511
Max	0.745	0.818	0.784	0.693	0.698	0.884	0.715	0.697	0.911

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7218.0	5545.1	1410.0	270.9	1079.6	930.9	103.0	45.2
Std Dev	72.4	64.5	34.9	3.5	54.7	51.3	13.1	2.5
Median	7215.5	5540.5	1409.5	270.7	1082.5	938.0	103.5	45.2
Min	7026.0	5381.0	1315.0	263.4	952.0	825.0	69.0	40.2
Max	7401.0	5705.0	1495.0	279.9	1236.0	1087.0	133.0	51.9

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8297.6	7218.0	122.6	957.0	103.0	1410.0	0.883	0.870	627.5
Std Dev	97.5	72.4	9.5	52.8	13.1	34.9	0.006	0.006	29.2
Median	8309.5	7215.5	123.0	963.5	103.5	1409.5	0.883	0.869	630.5
Min	8033.0	7026.0	95.0	841.0	69.0	1315.0	0.867	0.854	545.0
Max	8512.0	7401.0	148.0	1112.0	133.0	1495.0	0.896	0.883	726.0

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Appendix E. Case4a: Variable Order and Shipping Time

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Var: 4 + exp(16) = mean 20 Days		
Priority Repair:	No	Routine OST:	Var: 4 + exp(16) = mean 20 Days		
Cannibalization:	No	WRA Allowances:	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.630	0.628	0.568	0.625	0.639	0.698	0.611	0.622	0.708
Std Dev	0.090	0.087	0.108	0.042	0.035	0.103	0.052	0.055	0.108
Median	0.637	0.632	0.577	0.631	0.641	0.705	0.615	0.623	0.722
Min	0.359	0.397	0.309	0.520	0.533	0.427	0.468	0.462	0.400
Max	0.814	0.811	0.755	0.735	0.726	0.905	0.709	0.736	0.913

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7280.5	5562.3	1453.5	271.7	1014.4	904.7	64.0	44.0
Std Dev	83.6	74.0	38.6	3.9	49.6	47.4	10.2	2.3
Median	7282.5	5559.5	1456.5	271.4	1014.0	904.5	64.5	44.2
Min	7041.0	5376.0	1374.0	263.8	886.0	768.0	30.0	37.6
Max	7520.0	5770.0	1541.0	282.9	1126.0	1009.0	92.0	49.0

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8295.0	7280.5	122.3	892.2	64.0	1453.5	0.891	0.878	596.8
Std Dev	100.7	83.6	11.8	48.8	10.2	38.6	0.005	0.005	28.5
Median	8294.5	7282.5	122.0	890.5	64.5	1456.5	0.891	0.878	600.0
Min	8025.0	7041.0	92.0	769.0	30.0	1374.0	0.879	0.865	515.0
Max	8536.0	7520.0	155.0	988.0	92.0	1541.0	0.905	0.893	653.0

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Appendix F. Case4b: Variable Order and Shipping Time

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Var: 4 + exp(5) = mean 9 Days		
Priority Repair:	No	Routine OST:	Var: 4 + exp(23) = mean 27Days		
Cannibalization:	No	WRA Allowances:	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.630	0.621	0.556	0.631	0.647	0.695	0.611	0.612	0.736
Std Dev	0.076	0.088	0.101	0.036	0.027	0.083	0.045	0.055	0.080
Median	0.646	0.632	0.547	0.630	0.649	0.701	0.613	0.620	0.743
Min	0.399	0.360	0.361	0.554	0.577	0.505	0.490	0.492	0.477
Max	0.790	0.822	0.761	0.701	0.715	0.881	0.737	0.727	0.880

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7252.0	5566.4	1422.5	271.8	1046.7	911.6	88.3	44.6
Std Dev	78.3	68.0	33.8	3.6	46.1	40.0	13.5	2.1
Median	7250.5	5565.5	1421.5	272.0	1045.5	905.0	87.5	44.4
Min	7080.0	5359.0	1308.0	261.6	951.0	806.0	59.0	39.7
Max	7442.0	5704.0	1507.0	280.0	1181.0	1019.0	139.0	50.5

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8298.7	7252.0	124.9	921.8	88.3	1422.5	0.887	0.874	604.3
Std Dev	87.6	78.3	10.2	44.8	13.5	33.8	0.005	0.005	24.6
Median	8298.5	7250.5	126.0	919.0	87.5	1421.5	0.888	0.874	604.0
Min	8045.0	7080.0	100.0	820.0	59.0	1308.0	0.871	0.858	539.0
Max	8536.0	7442.0	144.0	1052.0	139.0	1507.0	0.898	0.884	672.0

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Appendix G. Case4c: Variable Order and Shipping Time

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Var: 4 + exp(18) = mean 22 Days		
Priority Repair:	No	Routine OST:	Var: 4 + exp(32) = mean 36 Days		
Cannibalization:	No	WRA Allowances:	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.541	0.543	0.475	0.527	0.571	0.585	0.514	0.524	0.593
Std Dev	0.111	0.118	0.096	0.064	0.038	0.127	0.085	0.080	0.124
Median	0.537	0.546	0.473	0.533	0.571	0.588	0.523	0.530	0.595
Min	0.269	0.276	0.178	0.368	0.468	0.286	0.265	0.312	0.238
Max	0.774	0.814	0.713	0.669	0.652	0.866	0.660	0.706	0.865

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7125.3	5505.7	1361.8	268.5	1111.1	926.9	135.5	45.3
Std Dev	84.4	74.4	30.9	4.2	57.8	53.7	20.4	2.9
Median	7126.0	5504.5	1364.5	269.0	1115.0	927.5	136.0	45.4
Min	6917.0	5308.0	1295.0	254.6	951.0	794.0	83.0	39.2
Max	7316.0	5711.0	1444.0	282.4	1232.0	1044.0	190.0	52.7

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8236.4	7125.3	124.1	987.0	135.5	1361.8	0.878	0.865	637.0
Std Dev	105.6	84.4	12.0	56.4	20.4	30.9	0.006	0.006	31.3
Median	8248.5	7126.0	125.0	992.5	136.0	1364.5	0.878	0.865	639.5
Min	8005.0	6917.0	93.0	838.0	83.0	1295.0	0.866	0.852	558.0
Max	8460.0	7316.0	154.0	1112.0	190.0	1444.0	0.895	0.882	739.0

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Appendix H. Case5: Prioritized Repair

Simulation Settings

Support Period	90 Days	**Variable TAT:**	No	**Runs:**	100
Flight Schedule:	Wartime	**Hi-Priority OST:**	Static 20 Days		
Priority Repair:	Yes, EXREP = .5*TAT	**Routine OST:**	Static 20 Days		
Cannibalization:	No	**WRA Allowances:**	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.686	0.662	0.650	0.717	0.746	0.685	0.699	0.698	0.721
Std Dev	0.076	0.077	0.087	0.036	0.026	0.107	0.051	0.041	0.120
Median	0.696	0.668	0.663	0.720	0.747	0.684	0.708	0.700	0.731
Min	0.484	0.469	0.406	0.628	0.684	0.321	0.513	0.542	0.424
Max	0.822	0.818	0.801	0.784	0.797	0.906	0.790	0.776	0.930

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7420.4	5709.8	1443.2	278.4	878.1	790.1	70.3	19.2
Std Dev	77.0	63.8	34.1	3.3	40.4	37.6	12.0	1.0
Median	7420.0	5704.5	1442.0	277.9	876.5	789.5	70.0	19.3
Min	7266.0	5572.0	1360.0	271.5	776.0	683.0	47.0	16.5
Max	7643.0	5868.0	1531.0	286.8	1008.0	903.0	102.0	22.0

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8298.5	7420.4	122.6	755.5	70.3	1443.2	0.908	0.894	458.9
Std Dev	89.1	77.0	12.2	37.4	12.0	34.1	0.004	0.004	23.3
Median	8293.0	7420.0	121.0	755.5	70.0	1442.0	0.907	0.894	454.5
Min	8109.0	7266.0	94.0	671.0	47.0	1360.0	0.898	0.880	413.0
Max	8536.0	7643.0	163.0	852.0	102.0	1531.0	0.917	0.906	528.0

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Appendix I. Case6: Variable Turn Around Time

Simulation Settings

Support Period	90 Days	**Variable TAT:**	Yes	**Runs:**	100
Flight Schedule:	Wartime	**Hi-Priority OST:**	Static 20 Days		
Priority Repair:	No	**Routine OST:**	Static 20 Days		
Cannibalization:	No	**WRA Allowances:**	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.606	0.601	0.552	0.526	0.631	0.659	0.505	0.540	0.646
Std Dev	0.092	0.101	0.108	0.053	0.046	0.121	0.077	0.094	0.123
Median	0.609	0.614	0.544	0.529	0.630	0.664	0.521	0.540	0.660
Min	0.285	0.295	0.256	0.369	0.491	0.320	0.311	0.308	0.313
Max	0.781	0.869	0.800	0.621	0.740	0.891	0.668	0.789	0.868

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7176.1	5464.1	1444.3	256.8	1101.4	971.8	70.0	48.6
Std Dev	88.3	76.2	33.0	5.0	64.2	59.1	10.6	4.0
Median	7183.5	5473.0	1440.5	256.3	1104.5	975.5	70.0	48.5
Min	6895.0	5237.0	1362.0	246.8	889.0	794.0	47.0	35.5
Max	7402.0	5670.0	1533.0	270.9	1275.0	1133.0	98.0	57.4

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8277.5	7176.1	122.5	979.0	70.0	1444.3	0.880	0.867	444.3
Std Dev	98.6	88.3	11.1	61.9	10.6	33.0	0.007	0.007	27.6
Median	8282.0	7183.5	123.5	978.0	70.0	1440.5	0.880	0.867	440.0
Min	8069.0	6895.0	96.0	762.0	47.0	1362.0	0.862	0.849	378.0
Max	8490.0	7402.0	145.0	1131.0	98.0	1533.0	0.905	0.891	540.0

Note: 81% of all repair actions used Variable TAT based on >= 10 Observations
19% of all repair actions used Static TAT from ARROWs based on < 10 Observations

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Appendix J. Case7: Cannibalizatior

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Static 20 Days		
Priority Repair:	No	Routine OST:	Static 20 Days		
Cannibalization:	Yes	WRA Allowances:	ARROWs		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Mean	0.680	0.683	0.588	0.688	0.767	0.678	0.684	0.682	0.739
Std Dev	0.053	0.063	0.099	0.029	0.017	0.114	0.041	0.040	0.081
Median	0.685	0.691	0.585	0.688	0.769	0.691	0.684	0.679	0.749
Min	0.552	0.426	0.313	0.616	0.730	0.351	0.552	0.570	0.416
Max	0.791	0.878	0.825	0.757	0.807	0.895	0.762	0.787	0.939

Cannibalization Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Mean	14.0	17.3	7.5	81.8	226.2	2.9	50.0	48.1	4.9
Std Dev	5.0	6.6	4.0	11.0	17.4	2.5	10.5	9.8	3.2
Median	14.0	17.0	7.0	82.5	225.0	2.0	50.0	47.5	4.0
Min	2.0	4.0	0.0	60.0	181.0	0.0	25.0	23.0	0.0
Max	27.0	37.0	19.0	106.0	272.0	12.0	88.0	73.0	15.0

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7340.8	5618.7	1459.9	274.4	1005.9	891.5	71.9	43.5
Std Dev	76.3	74.8	37.2	3.7	45.2	43.4	10.7	2.1
Median	7342.5	5619.5	1456.5	274.6	1009.5	892.5	72.0	43.5
Min	7120.0	5438.0	1352.0	265.7	876.0	780.0	48.0	38.6
Max	7510.0	5788.0	1569.0	282.3	1107.0	1003.0	115.0	48.9

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8346.7	7340.8	124.0	881.9	71.9	1459.9	0.893	0.880	609.6
Std Dev	89.4	76.3	11.6	41.4	10.7	37.2	0.005	0.005	26.0
Median	8356.5	7342.5	122.5	882.0	72.0	1456.5	0.892	0.879	603.5
Min	8092.0	7120.0	95.0	765.0	48.0	1352.0	0.881	0.868	544.0
Max	8562.0	7510.0	160.0	979.0	115.0	1569.0	0.904	0.892	680.0

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Appendix K. Case8: AVCAL vice ARROWs Allowances

Simulation Settings

Support Period	90 Days	Variable TAT:	No	Runs:	100
Flight Schedule:	Wartime	Hi-Priority OST:	Static 20 Days		
Priority Repair:	No	Routine OST:	Static 20 Days		
Cannibalization:	No	WRA Allowances:	AVCAL		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Target Ao	0.600	0.600	0.560	0.560	0.640	0.660	0.560	0.600	0.660
Mean	0.662	0.739	0.663	0.728	0.778	0.734	0.717	0.800	0.798
Std Dev	0.072	0.066	0.096	0.039	0.023	0.120	0.038	0.041	0.082
Median	0.654	0.742	0.673	0.737	0.776	0.758	0.723	0.803	0.811
Min	0.503	0.521	0.457	0.625	0.708	0.348	0.597	0.631	0.543
Max	0.839	0.863	0.841	0.808	0.829	0.914	0.784	0.882	0.937

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7626.5	5882.7	1468.0	287.3	679.1	599.7	51.0	29.4
Std Dev	73.8	62.7	37.6	3.1	42.4	38.7	8.9	1.9
Median	7618.5	5876.0	1469.5	287.5	675.5	598.5	51.0	29.1
Min	7436.0	5744.0	1381.0	280.2	595.0	510.0	33.0	25.3
Max	7800.0	6043.0	1555.0	294.3	793.0	706.0	80.0	33.8

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	8305.6	7626.5	38.2	640.9	51.0	1468.0	0.923	0.918	470.4
Std Dev	88.8	73.8	6.1	42.1	8.9	37.6	0.005	0.005	26.4
Median	8300.5	7618.5	38.0	638.0	51.0	1469.5	0.923	0.919	469.5
Min	8067.0	7436.0	27.0	554.0	33.0	1381.0	0.910	0.905	410.0
Max	8541.0	7800.0	57.0	751.0	80.0	1555.0	0.932	0.928	527.0

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Appendix L. Case9: Full Simulation

Simulation Settings

Support Period	180 Days	Variable TAT:	Yes	Runs:	100
Flight Schedule:	Actual	Hi-Priority OST:	Var: 4 + exp(18) = mean 22 Days		
Priority Repair:	No	Routine OST:	Var: 4 + exp(32) = mean 36 Days		
Cannibalization:	Yes	WRA Allowances:	AVCAL		

Ao Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Mean	0.781	0.813	0.653	0.949	0.915	0.636	0.951	0.877	0.787
Std Dev	0.058	0.061	0.120	0.020	0.013	0.114	0.025	0.034	0.081
Median	0.781	0.817	0.678	0.956	0.916	0.642	0.959	0.880	0.807
Min	0.643	0.634	0.367	0.889	0.876	0.412	0.849	0.780	0.493
Max	0.915	0.922	0.827	0.973	0.940	0.874	0.979	0.945	0.911

Cannibalization Statistics

	E2C2	EA6B	ES3A	F14B	FA18C	HH60H	RF14B	S3B	SH60F
Mean	12.8	11.8	8.6	6.6	96.4	7.9	2.9	12.0	5.4
Std Dev	5.8	5.9	4.9	4.3	14.4	4.5	2.9	6.1	3.9
Median	13.0	11.0	7.5	6.0	96.0	8.0	2.0	11.0	5.0
Min	0.0	2.0	1.0	0.0	66.0	0.0	0.0	2.0	0.0
Max	33.0	27.0	24.0	24.0	133.0	22.0	17.0	27.0	17.0

AIMD Statistics

	Stock Inductions	Stock Repairs	Stock BCMs	Time Avg # of Stock In Repair	EXREP Inductions	EXREP Repairs	EXREP BCMs	Time Avg # of EXREPs In Repair
Mean	7390.4	5817.0	1550.3	142.8	376.6	315.8	60.6	8.8
Std Dev	78.4	74.8	37.3	3.0	32.8	30.8	10.0	1.1
Median	7385.0	5821.5	1551.0	142.8	376.5	318.0	59.5	8.8
Min	7210.0	5643.0	1436.0	136.1	320.0	257.0	38.0	6.2
Max	7626.0	5971.0	1640.0	149.6	472.0	417.0	91.0	11.8

Supply Dept. Statistics

	Demands	Issues	Not Carried	Not In Stock	DTO Reqns	Stock Reqns	Net Eff	Gross Eff	Stock Diversions
Mean	7767.0	7390.4	41.2	335.4	60.6	1550.3	0.957	0.952	186.3
Std Dev	84.7	78.4	6.9	31.4	10.0	37.3	0.004	0.004	15.4
Median	7775.5	7385.0	40.0	335.0	59.5	1551.0	0.957	0.951	185.5
Min	7557.0	7210.0	28.0	276.0	38.0	1436.0	0.945	0.940	154.0
Max	7988.0	7626.0	57.0	430.0	91.0	1640.0	0.964	0.959	236.0

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